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Empirical Findings On Persuasiveness Of Recommender Systems For Customer Decision Support In Electronic Commerce

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EMPIRICAL FINDINGS ON PERSUASIVENESS OF RECOMMENDER SYSTEMS FOR CUSTOMER DECISION SUPPORT IN ELECTRONIC COMMERCE

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More and more companies are making online presence by opening online stores and providing customers with company and products information but the overwhelming amount of information also creates information overload for the customers. Customers feel frustrated when given too many choices while companies face the problem of turning browsers into actual buyers. Online recommender systems have been adopted to facilitate customer product search and provide personalized recommendation in the market place. The study will compare the persuasiveness of different online recommender systems and the factors influencing customer preferences.

Review of the literature does show that online recommender systems provide customers with more choices, less effort, and better accuracy. Recommender systems

using different technologies have been compared for their accuracy and effectiveness. Studies have also compared online recommender systems with human recommendations and recommendations from expert systems. The focus of the comparison in this study is on the recommender systems using different methods to solicit product preference and develop recommendation message. Different from the technology adoption and acceptance models, the persuasive theory used in the study is a new perspective to look at the end user issues in information systems.

This study will also evaluate the impact of product complexity and product involvement on recommendation persuasiveness. The goal of the research is to explore whether there are differences in the persuasiveness of recommendation given by different recommender systems as well as the underlying reasons for the differences. Results of this research may help online store designers and ecommerce participants in selecting online recommender systems so as to improve their products target and advertisement efficiency and effectiveness.

DEDICATION

I would like to dedicate this research to my parents, who have been the source of strength and support through out this doctoral program. It would have been impossible to follow this dream of becoming a college professor if it were not for their constant and loving support.

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CHAPTER I

INTRODUCTION

The purpose of this chapter is to lay the foundation for a dissertation. This chapter provides an overview of electronic commerce, decision support systems and intelligent agents, online recommendation systems, and the persuasion theories. The research problem statement, research questions, and research methodology are included. Finally, the implications of the study and organization of the dissertation are presented.

Overview

With the growing popularity of the Internet and the prosperity of electronic commerce (e-commerce), traditional trading behavior patterns have significantly changed (GVU, 1999). For instance, pre-purchase information searching and online shopping are becoming more popular. However, the exponentially increasing information provided by Internet enterprises is both a blessing and a curse. More information may allow customers to select product options that better match their personal preferences than they would otherwise. On the other hand, having access to too much information may cause information overload and frustration with the different information sources provided by the Internet. While online businesses compete for customer time and attention, information overload can be a threat to customer satisfaction and loyalty (Lee, Liu, and Lu, 2002; Maes, Butmann, and Moukas, 1999; Reibstein, 2002). Online businesses need to provide exceptional value and services based on customer needs if they want customer information browsing at their online store to finally lead to persuaded purchase behavior. One way to overcome such a problem is to build personalized recommender systems using intelligent agents and good user interfaces to retrieve product information that really interests the customers (Desharnais, Lu, and Radhakrishnan, 2002).

Recommender systems are interactive decision support systems that assist consumers in the initial screening of alternatives available in online stores (Haubl, and Trifts, 2000). A highly persuasive recommender system will work as a persuasive salesperson. They provide recommendations for product search and selection (Detlor, and Arsenault, 2002; O'Keefe, and McEachern, 1998), product customization (Grenci, and Todd, 2002) and tell the customer what to buy or who to buy from (Ansari, Essegaier, and Kohli, 2000; Maes *et al.*, 1999). The products can be recommended based on the top overall sellers on a site, on the demographics of the consumer, or on an analysis of the past buying behavior of the consumer as a prediction for future buying behavior. Recommender systems enable customers to cope with information complexity and information overload (Chiasson, and Dexter, 2001; Hanani, Shaira, and Shoval, 2001; Nwana, and Azarmi, 1997), reduce effort, improve the effectiveness and efficiency of customer decision-making (Haubl *et al.*, 2000; Lynch, and Ariely, 2000), and help to configure customized products (Grenci *et al.*, 2002). Different forms of recommender systems are currently implemented on the website of a number of online retail stores (e.g., www.macys.com, www.netmarket.com, www.amazon.com, www.dell.com, www.personalogic.com).

One of the central issues regarding recommender systems is their *persuasiveness* (Komiak, and Benbasat, 2004). Persuasiveness refers to the extent to which customers are moved or influenced by a given recommender system, which is defined here as the reasoning provided by recommender systems regarding the fit of product features with personal needs. Persuasiveness of decision support systems/recommender systems may vary when customer expertise and product complexity vary (Gregor, and Benbasat, 1999; Huang, Chung, Barbara, and Chen, 2004; Jiang, Klein, and Vedder, 2000; Mao, and Benbasat, 2000). Persuasiveness reflects the power of a recommender system as a customer decision support system. It is important because customer (particularly those with limited expertise) confidence in the recommender system, self-confidence in decisions, and the differences between customer and recommender system opinions are all related to the persuasive power of the system (Jiang et al., 2000). Decision support systems are usually not used efficiently by decision makers because of a lack of confidence in the recommendations they provide (Moulin, Irandoust, Belanger, and Desbordes, 2002). In the context of e-commerce customer purchase decision making, a time lag usually exists between the time such a decision must be made and when the customer can physically obtain the product and become aware of its quality. As a result, the acceptance of a recommender system product recommendation is more likely to be determined by its persuasiveness rather than by its correctness (The match between the product delivered and their searching criteria). Therefore, it is important for a recommender system to convince the customer that its recommendation is relevant, justified and useful. If designers and owners of online stores know which type of recommender system is more persuasive for certain type of products and why, more persuasive recommender systems could be designed and built.

Over the past decade, a number of researchers have studied the influence of trust, explanation and transparency on end user confidence in decisions provided by recommender systems as well as other types of decision support systems. Table 1 showed a list of empirical researches done with research method and results on the use of recommender systems (Sinha, and Swearingen, 2002; Wang, and Benbasat, 2003; Ye, and Johnson, 1995)

Table 1. Summary of Recommender Systems Research

Study	Research method	Results
Todd and Benbasat, 1992	Lab experiment	The use of a decision aid may result in effort saving but not improved decision performance.
Morris, 1994	Lab experiment	An expert system-based tool is preferred for company information databases search in terms of accuracy and consistency of recommendations, ease of use, confidence in recommendation and time taken.
Ye and Johnson,1995	Lab experiment	Explanation of reasoning process convinces decision maker of the recommendation soundness.
O'Keefe and McEachern, 1998	Case study	Development of an online customer decision-making process to suggest points of recommendation agent support.
Schafer et al., 1999	Case study	Taxonomy of recommender systems was created and five commonly used e-commerce recommender application models described.
Ansari et al., 2000	Lab simulation	Internet recommender systems can model customer preferences by using five types of information: a person's expressed preferences, preferences of other consumers, expert evaluations, item characteristics, and individual characteristics.
Haubl and Trifts, 2000	Lab experiment	Recommender systems may improve individuals' choice outcomes in online shopping decision.
Herlocker, 2000	Lab simulation	Recommender systems have not been used in high-risk decision-making because of a lack of transparency.
Jiang, 2000	Lab experiment	For naïve users, the confidence in the source of expertise, self-confidence, and the degree of discrepancy between the user's opinion and that of the expert system are all related to the persuasive power of the system.
Chiasson and Dexter, 2001	Case study	Recommender systems enable customers to cope with information complexity and information overload.

Table 1. (continued)

Desharnais et al., 2002	Lab simulation	Agents can provide tailored product recommendations by filtering information on behalf of their users and reduce the information overload; vendors could use for price negotiation with the customers.
Rashid et al., 2002	Lab experiment	Learning techniques of recommender systems affects the user effort and prediction accuracy.
Cosley et al., 2003	Lab experiment	Users rate consistently across rating scales. Users can be manipulated by the expert system prediction. Users can detect expert system predication manipulation.
Gershoff, et al., 2003	Lab experiment	Consumers pay special attention to extreme opinion agreement when assessing recommendation agent diagnosticity. Positive extreme agreement is more influencial than negative.
Wang and Benbasat, 2004	Lab experiment	Consumers' initial trust not only directly influences their intention to adopt the recommendation agents but has indirect effect via their enhanced perceived usefulness of the agents.
Swaminathan, 2003	Lab experiment	Category risk moderates the impact of recommendation agents on decision quality and product complexity moderates the role of recommendation agents on amount of search.
Benbasat, 2004	Lab experiment	Different types of explanation in recommender systems increase different trusting beliefs.
Porntpitakpa, 2004	Review	A high-credibility source is superior over a low-credibility on persuasion.
Huang et al., 2004	Lab simulation	Combining product content information and historical customer transaction information achieved more accurate prediction and relevant recommendation than using only collaborative information.
Yoon and Lee, 2004	Lab experiment	The product category, display format and other peripheral information provided by the p2p recommender system affect the behaviors of the potential customers.
Wang and Benbasat, 2005	Lab experiment	Consumer trust in recommender agents is an integral factor influencing their successful adoption.

The studies showed that recommender systems provide better decision support with less user effort in information search. However, the outcomes of recommender systems typically depend on the context of the decision, the presentation of the recommendation, characteristics of the user, the object of the recommendation, and the user perceptions regarding the recommender systems. Learning techniques used by different recommender systems can affect user effort and prediction accuracy (Rashid, Albert, Cosley, Lam, McNee, Konstan, and Riedl, 2002). Combining product content information and historical customer transaction information achieved better prediction accuracy and recommendation relevance than using only collaborative information (Huang et al., 2004). Product complexity moderates the role of recommender systems on amount of search in online shopping by reducing the amount of search when the number of attributes used to describe a product is fewer (Swaminathan, 2003).

Given the benefits and increased use of recommender systems in the market place, it is necessary to study how different recommender systems influence customer preferences by comparing the persuasiveness of different recommender systems and probing the reasons behind it.

Evolution of Internet-Based Electronic Commerce

Since the introduction of the Internet in 1969 and the development of the World Wide Web in the early 1990's, the growing number of interconnected computers worldwide has provided Internet users with the potential to access an increasing abundance of information on a variety of subjects and providers. Internet usage has expanded from early academic research and technical development to both business and home users. It is not only perceived as a system able to send and receive information, but also as a tool for conducting business. According to the latest GVU survey by the Graphic, Visualization, and Usability Center at Georgia Institute of Technology (1999), the frequency of Internet usage (including hours on Internet for work and fun) for individuals has increased significantly. Additionally, more and more organizations (Bottoms, 1995; Clancy, 1995; Tetzeli, 1994) are using the Internet for advertising and interacting with customers.

Broader business use of the Internet became possible in the early 1990s through the efforts of a private consortium called the Commercial Internet Exchange Association (CIX) (Cross, 1994). The CIX persuaded the Internet community that commercialism was essential to its further development (Cross, 1994). Following this and the growing number of new Internet users, companies immediately began to establish a commercial presence on the Internet. The most prevalent method used was the development of a home page via a web site. According to a study conducted by Liu et. al. (1997), companies commonly include five elements on their web site: 1) information about products and services, 2) a company overview, 3) a customer feedback form, 4) a “what’s new” area, and 5) an overview of financial information.

Encouraged by the promise of reaching new sales markets and enhancing operational efficiency, millions of international firms ranging in size from local, single proprietor businesses to multinational corporations have established their presence on the

Internet via a web site. Many of these firms are already using their customized web site to support online business transactions involving both trading partners and direct customers. This breaks down the restriction of geographical consideration or lack of shelf space for the suppliers and brings about a broad range of customer choices. Yet new problems are encountered. It is hard for consumers to find their way in a large market place where so many suppliers and products are offered.

A filtering scheme like a recommender system is one solution that can propose relevant shops and products to a consumer based on customer preferences or the recommendation of like-minded people. The personalization of information provided by recommender systems can reduce consumer search effort and increase the purchase decision quality.

Development of Decision Support Systems and Intelligent Agents

Decision support systems (DSS) are computer technology solutions that can be used to support complex decision making and problem solving (Shim, Warkentin, Courtney, Power, Sharda, and Carlsson, 2002). Since the early 1970s, DSS technology and applications have evolved significantly. Many technological and organizational developments have impacted this evolution.

DSS once utilized more limited database, modeling, and user interface functionality, but technological innovations have enabled far more powerful DSS applications. Beginning in about 1990, Inmon and Kimball actively promoted data-driven DSS that were built using relational database technologies. In the early 1990s, a major technology shift occurred from mainframe-based DSS to client/server-based DSS. In 1994, Data Base Management Systems (DBMS) venders began implementing Online Analytical Processing (OLAP) capabilities into their databases (Powell, 2001). In 1995, web-based and web-enabled DSS began impacting practitioners and academics interested in decision support technologies (Bhargava, and Power, 2001; Power, 2000).

Early DSS supported individual decision-makers and included the model-oriented DSS, expert systems, multidimentional analysis, query and reporting tools, OLAP, business intelligence, and executive information systems. Later, DSS technologies were applied to workgroups or teams, the most exotic being applied to virtual teams (Shim et al., 2002). The next decade of DSS included more active decision support (Keen, and Morton, 1987) because organizations were becoming more agile and flexible while information sources for decision support were becoming more easily accessible and overwhelming in amount.

Intelligent systems are the new technology platforms that could be an alternative solution to this problem of active decision support. Rather than stand-alone artificial intelligence, intelligent logic is now usually inherent in the processing of all decision support systems. Intelligent systems are built to fulfill two key purposes: 1) the screening, sifting and filtering of a growing overflow of data, information and knowledge, 2) the support of an effective and productive use of standard software (Shim et al., 2002). Intelligent agents address the problem of data screening by filtering data sources for user-defined search profiles, identifying and accessing relevant data, copying the data, and organizing and storing it in a data warehouse.

For electronic commerce, intelligent agents can help automate a variety of activities, mostly time-consuming ones. Benefits include lower customer search effort, improved decision quality, and lower the transaction costs. Intelligent agents may be categorized as personalized, social, continuously running and semi-autonomous (Guttman, Mouksas, and Maes, 1998b) and make e-commerce more user-friendly, semi-intelligent and human-like. These qualities are conducive for optimizing the whole buying experience and revolutionizing commerce (Jeffrey, 1997).

The normative model of consumer buying process can be described as a learning, information-processing and decision-making activity divided in several sequent steps: need recognition, information search, alternative valuation, purchase decision and after purchase evaluation (Bettman, 1979; Boyd, Walker, Mullins, and Larreche, 2002; Brassington, and Pettitt, 2003; Dibb, Simkin, Pride, and Ferrell, 2001; Jobber, 2001; Kotler, 2003; O'Keefe *et al.*, 1998). Most academics and practitioners agree that demographic, socio-economic, cultural, psychological and other personal factors, largely beyond the control and influence of the marketer, have a major effect on consumer buying behavior (Boyd *et al.*, 2002; Czinkota, and Kotabe, 2001; Dibb *et al.*, 2001; Harrell, and Frazier, 1999; Jobber, 2001; Solomon, and Stuart, 2003). Despite their incapacity to exercise any substantial influence on the above factors, marketers can use marketing tools to influence consumer buying behavior and the final outcome of buyer-seller interaction (Brassington *et al.*, 2003; Kotler, 2003).

With the expansion of virtual markets, considerable research effort has been focused on moderating the online buying and decision-making process (Joines, Scherer, and Scheufele, 2003; Liao, and Cheung, 2001; Liu, and Arnett, 2000; McKnight, Choudhury, and Kacmar, 2002; Miles, Howes, and Davis, 2000; O'Cass, and Fenech, 2003). Compared to the traditional marketing place, online shopping includes a new step of building trust or confidence (Lee, 2002; Liang, and Lai, 2002; Liebermann, and Stashevsky, 2002; McKnight *et al.*, 2002; Suh, and Han, 2002). Chaung et al. (2003) identified two groups of factors associated with online consumer behavior, uncontrollable factors (consumer characteristics and environmental influences) and controllable factors (product/service characteristics, medium characteristics, and merchant/intermediary characteristics).

As the customer decision-making process is increasingly information-intensive with more information and multiple information sources, online recommender systems can be used as online marketer's persuasion tools to influence need recognition, information search and evaluation. The recommender systems can provide inputs for the consumers' black box where information is processed before the final consumer's decision is made so as to help consumers make better purchasing decisions.

Online Recommender Systems

Recommender systems provide a type of mass customization that is becoming increasingly popular on the Internet. Although the idea of recommender systems dates back to Negroponte (1970) and Kay (1984), practical implementation of "intelligent agents" is relatively recent and has been fueled by the success of online companies such as Firefly.com and Amazon.com. Early uses, which were not on the Internet, included short-lived in-store kiosks at Blockbuster Video that recommend films on the basis of member past rental history (West, Ariely, Bellman, Bradlow, Huber, Johnson, Kahn, Little, and Schkade, 1999). Magnet (Levy, 1993) claimed to be the first intelligent agent for the Macintosh. Essentially a file manager, it dispatched files into the trash if a user mistyped a destination folder (Foner, 1993).

Recommender systems are agents of the sort used by Blockbuster. Using behavioral or preference information, they filter alternatives and make suggestions to a user. Internet search engines are examples of content-based recommender systems, as these retrieve documents by means of keywords. In one commonly used system, the frequency of a target word is used to assess document relevance, and the relative frequencies of words are used to assess document similarity (Salton, and Buckley, 1988). Recommender systems screen attractive alternatives for individual-level predictions that can be useful even if there are a few alternatives. Recommender systems are most suitable for searching for goods which people do not always have the ability or the means to evaluate (e.g., cars and computers). Most important, recommender systems are able to work well with much less information because most people are averse to answering too many questions before they get recommendations (Ansari et al., 2000).

A number of researchers have categorized recommender systems according to different standards (Ansari *et al.*, 2000; Detlor *et al.*, 2002; Grenci *et al.*, 2002; Guttman, Moukas, and Maes, 1998a; Maes *et al.*, 1999; Montaner, Lopez, and de la Rosa, 2003; Mouksa, Zacharia, Guttman, and Maes, 2000). Among them, Ansari et al. divide recommender systems into collaborative filtering and content filtering based on the information sources of the recommendation. A second common classification of recommendation systems is based on whether they are designed to help a consumer determine what to buy or from whom to buy. These categories are product and merchant brokering, respectively (Guttman et al., 1998a; Maes et al., 1999). Another group of researchers introduced four types of recommender systems, based on the type of reasoning process: collaborative filtering recommender systems, constraint-satisfaction recommender systems, rule-based recommender systems and data-mining recommender systems (Ansari *et al.*, 2000; Detlor *et al.*, 2002; Grenci *et al.*, 2002; Maes *et al.*, 1999; Montaner *et al.*, 2003; Mouksa *et al.*, 2000). The classification of recommender systems defined by Ansari et al. (2000) will be used in this study to compare the persuasiveness of their recommendations. Although different reasoning processes could be used in the background by different online stores, the interfaces presented to the user are of two major types: those that need user input and those that do not. Therefore, this study will only compare two types of recommender systems, those that use content filtering vs. collaborative filtering for eliciting persuasiveness. The content filtering recommender systems require customer input. The collaborative filtering recommender systems depend on datamining of existing data.

Collaborative-filtering recommender systems utilize the opinions of like-minded people to generate product recommendation. These kinds of recommender systems first compare customer product ratings with those of other customers. After identifying the “nearest neighbors ” which are peer customers with similar tastes, the recommender system selects the products rated highly by chosen similar others (i.e. nearest neighbors). Since the customers may not yet have rated the item, this approach possibly leads to serendipitous findings (Ansari et al., 2000; Maes et al., 1999). Collaborative filtering requires a large amount of data to facilitate the correlation of consumer purchasing patterns, and recommendations cannot be changed or influenced by expert opinion. Thus, collaborative filtering is appropriate when decisions are not of significant importance, and is used primarily for products that are influenced by word-of-mouth. Until now, most of the uses for collaborative filtering have been with CDs, books, and music (Charlet, 1998b).

Content filtering is based on a system of selection logic rules that a retailer determines. Its biggest advantage over collaborative filtering is the ability to control the marketing process by creating rules. For instance, if a shopper has reviewed information on a new computer several times, a rule can be put in place to offer the shopper an extra 5% off if he purchases today. Also, it allows experts (i.e. customer managers) to tailor offers to certain shopper segments in order to offer relevant products and to maximize cross-selling opportunities. However, the system is only as good as programmer writes the rules, which implies continued maintenance costs (Charlet, 1998a).

Figures 1 and 2 are examples of a collaborative filtering recommender system used at Amazon.com. The recommendation will be built based on products rated by the customer for similar taste. The 1 to 5 star-Likert scale was used in this example. Figure 3 is an example of content filtering recommender system where the product recommendation will be based on customer input of product attributes.

The Amazon.com rating page prompts customers to rate items recently purchased. These ratings are used as input to a recommendation engine to help the customer find other items that she/he is likely to buy. Customers are asked to invest effort in rating in exchange for which they get more useful recommendations. In Figure 1, no item has been presented because the user is a new customer while in Figure 2, items purchased by the customer before have been presented and rated for the system to provide recommendations for new purchase.

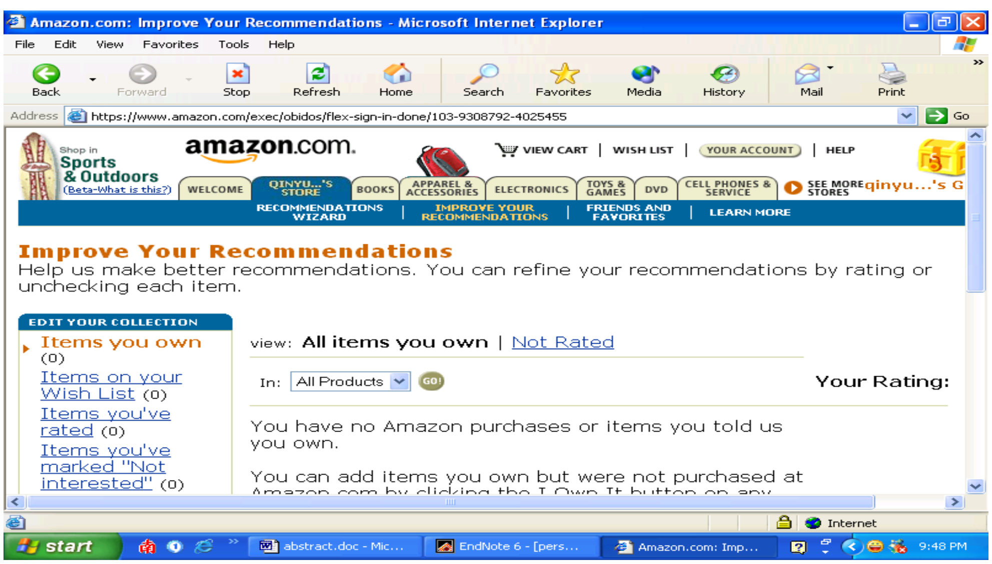

Figure 1. New Customer Recommender Interface at Amazon.com

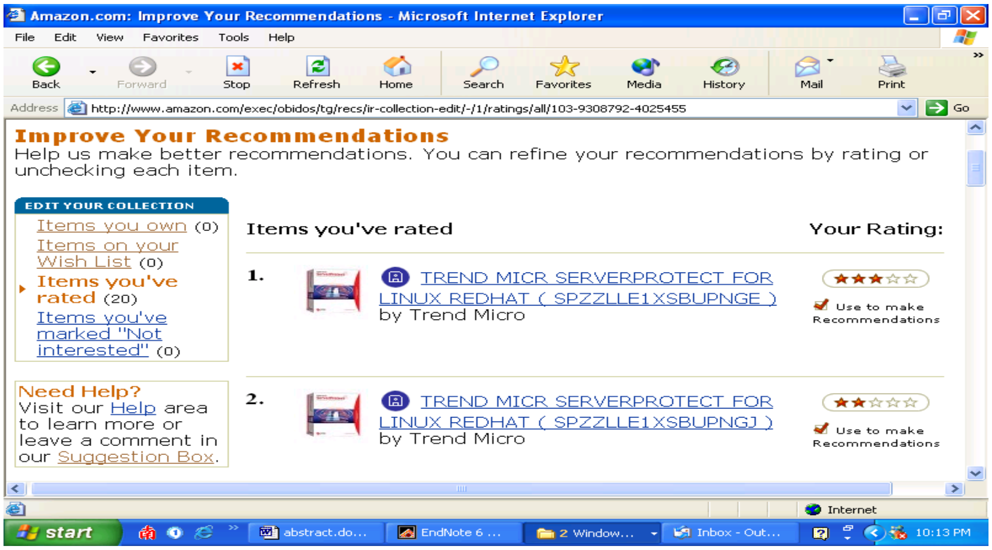

Figure 2. Customer with Rated Items for Recommendation Building

In Figure 3, the advisor feature at Dell.com allows customers to indicate their preferences category to search when purchasing a product.

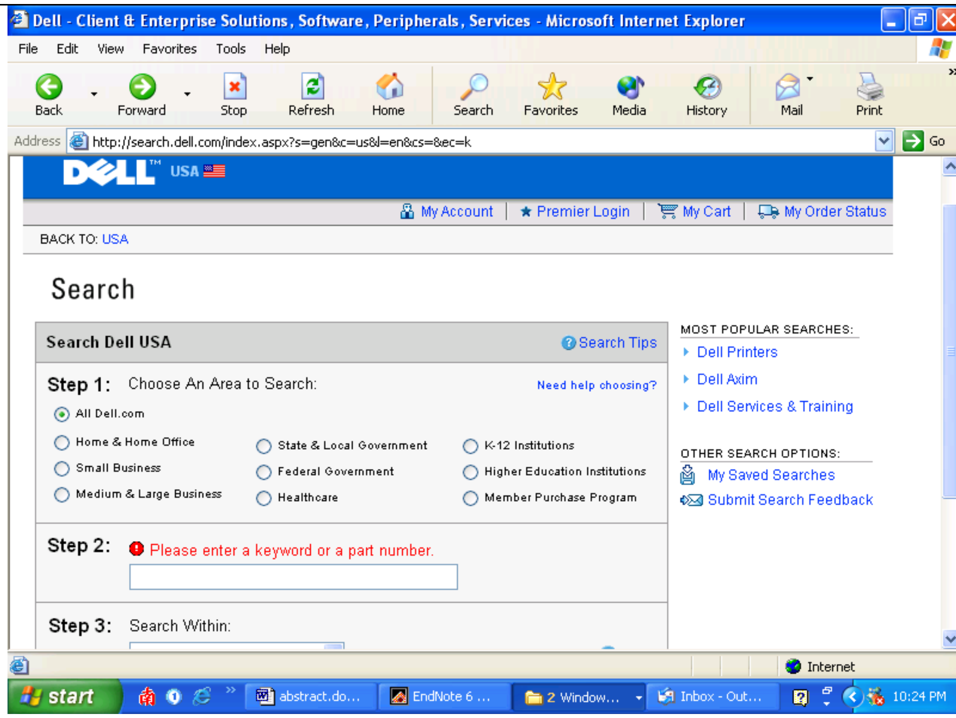

Figure 3. Customer Product Attributes/Constraints Input at Dell.com

Persuasion Theories

Persuasion, a concept originated from psychology and communication (Reardon, 1981), is the attempts to change the behavior of at least one person through symbolic interaction. It is conscious and occurs when both (a) a threat to goals of a subject is observed and (b) the source and degree of this threat are sufficiently important to warrant the expenditure of effort involved in persuasion (Reardon, 1991). It involves guiding people toward the adoption of some behavior, belief, or attitude preferred by the persuader through reasoning or emotional appeals. It is not a selection but presents a case for the adoption of a persuader-preferred mode of action, belief, or attitude. Persuasion is a bilateral, incremental activity that involves some strategizing. Therefore, although the goal of persuasion is to change attitudes and/or behavior, persuasion needs to be properly presented because most people are naturally protective of their views and their behaviors and can close their minds to change if persuasion is not addressed in an acceptable fashion.

There are two broad types of theories of persuasion. The first ones downplay the role of reasoning in human behavior and might be described as push-and-pull theories that describe people as torn between inconsistent cognitions, pushed by stimuli or pulled by rewards. The second group of persuasion theory takes into account the ability of people to consider their actions and to reason through messages encouraging them to change during the course of persuasion (Reardon, 1991).

The second group of theories focuses on different aspects of persuasion. Bandura's social learning theory (Bandura, 1977) explains how patterns of behavior are acquired and how these patterns are influenced by both the self and external sources of influence. It demonstrates how people learn from direct and vicarious experience. The elaboration likelihood model (ELM) (Petty, and Cacioppo, 1986) explains why certain aspects of persuasive messages are sometimes more powerful than others in bringing about behavioral changes. The impact of persuasive elements depends on the information-processing route used by the persuadee. Communication/persuasion matrix model demonstrates how factors such as source, message, receiver, channel, and destination variables can be manipulated to evoke the 12 steps needed to bring about persuasion (McGuire, 1985). The ELM can be seen as a complement to McGuire's model, because it informs the persuader as to the priority he or she might want to attribute to factors affecting the central route versus the peripheral route.

The Elaboration Likelihood Model (ELM) (Petty *et al.*, 1986) clarified the difference between content and other related cues in determining the credibility of the messages. The ELM argues that persuasion in a communication can be achieved via one of two routes: central or peripheral. The central route is closely related to delivering strong, valid messages, so it is related to the content of information and its deliberate cognitive arguments around information content. In the absence of a central route, the peripheral route is used. It is based on social and affective cues rather than on the basis of message context. The examples of peripheral routes are the social relationship to the source and the social context.

Jaccard's study of expert systems advice acceptance provides another model to understand the process of persuasion communication (Jaccard, 1981). He proposed three variables as immediate psychological determinants for belief change: discrepancy of judgments, self-confidence and the confidence in the source of system knowledge. According to Jaccard, a low discrepancy, lower self-confidence, and a higher confidence in the source should lead to a higher acceptance of the advice given by the expert system.

The Appropriateness-Consistency-Effectiveness (ACE) model applies when the persuader is hoping to encourage the persuadee to reason about his or her behavior

(Reardon, 1981; Reardon, 1987). It includes certain stimulus inducements that can operate to encourage the adoption of a new behavior and suggests three categories of inducements. The ACE model can provide insight into how messages might be developed that encourage the central route processing of information described in ELM. This model can also provide some assistance in message formulation directed at evoking liking or interest, comprehension, skill acquisition, and yielding. While the ELM focuses on how persuasive messages are received, the ACE model focuses on the types of messages likely to be persuasive.

As mentioned before, persuasion is a complex activity. Factors influencing the persuasiveness of a message can be tracked to the message itself, the persuader and the persuadee. How the source of the message is perceived, gender and personality of the persuader, and the rapport with the persuadee are the persuader factors. Message variables include order of arguments, evidence, style of presentation, and salience of issues. The persuadee's gender, emotional dispositions, cognitive complexity, expectations, and schemata contribute to the persuasion outcome (Reardon, 1991).

Studies have also identified several factors specific to persuasiveness of recommender systems in electronic commerce, such as product complexity, consumer knowledge, category risk (Swaminathan, 2003), items characteristics, individual characteristics, expert evaluations, preferences of other consumers, and a person's expressed preferences (Ansari et al., 2000). In this study, we will focus on the product complexity factor and its impact on recommender system persuasiveness.

Research Questions

The research on online recommender systems focuses on two aspects: the impact of recommender systems on both the quality and efficiency of consumer decision making in an online shopping environment (i.e., how good a choice the consumer makes given the set of available products and how much effort he or she must expend to make a decision) and the impact on consumer behavior of a recommender system that elicits limited preference information before making a personalized product recommendation (Haubl *et al.*, 2000). No published comparison within or across two types of recommender systems has been done. This study conducted the comparison of two different recommender systems, the content-based filtering and collaborative filtering, to study their persuasiveness and the possible reasons for the differences.

The study tried to offer tentative answers specific to three questions:

1. Are there differences between the persuasiveness of the recommendation given by the two online recommender systems?
2. What are the factors causing the differences in the persuasiveness?
3. What is the role of product complexity on the persuasiveness difference?

This study examined which type of recommender system is more persuasive in the context of e-commerce and why. The answer will be important to designers and owners of online stores in considering what recommender systems to use for certain products. The higher level of recommender system persuasiveness will also lead to higher acceptance by customers (Jiang et al., 2000).

Research Methodology

The research methodology section consists of a brief discussion of the research sample, the research instrument, and data analysis. A more in-depth discussion of the methodology is provided in Chapter III.

Research Sample and Design

The research sample of this study consists of a convenience sample of about one hundred undergraduate students from a major southern university. They were recruited to participate in a web-based experiment conducted in a computer lab. Respondents were told to search for two different products (high vs. low complexity) with two websites (www.amazon.com and www.activebuyersguide.com) using different recommender systems. To control for participant differences, a within-subject design with repeated measures was used. Each participant was asked to use two recommender systems, one at a time, to purchase two products. As an incentive for participating, the respondents were told that they will be given extra credits for taking part in the experiment. On completing each product search, participants filled out a survey with questions intended to measure appropriateness, consistency, effectiveness, and their perception of the recommender systems persuasiveness. Other data such as age, gender, consumer product involvement with each product and experiences with online shopping were collected for analysis. A pilot study was conducted for testing of the instrument before data collection from the main sample.

Covariate

Product involvement is a factor that may influence consumers' cognitive and behavioral response-including memory, attention, processing, search, brand commitment, satisfaction, early adoption, and opinion leadership (Laaksonen, 1994). According to Zaichowsky (1985), product involvement is the relevance that individuals perceived in a product, according to their inherent values, interests, and needs. If consumers feel that a product is important to their life, they will be more likely to process the communication along the central route and expend more effort processing or understanding the message. Product involvement represents one of the main motivations to process communications.

The concept of product involvement has been receiving more research attention recently to study consumers' response to Internet advertising (Ahn, and Edwards, 2002; Cho, and Leckenby, 1999; Karson, and Korgaonkar, 2001; Laczniak, Kempf, and Muehling, 1999; Yoo, and Stout, 2001). Studies also indicated that consumer's involvement influences consumer flow experience and subsequent exploratory search behavior (Hoffman, and Novark, 1996; Koufaris, Kambil, and LaBarbera, 2001-2002; Quester, and Smart, 1998). Involved consumers are more diligent in examining and detecting differences among brands (Zaichowsky, 1985). Highly involved consumers use a central route in information process. Cho (1999) found support that product involvement influenced subjective motivation to processing web advertising content. Product involvement also affect the relationship between online advertisement interactivity and consumer comprehension (Macias, 2003). It was also pointed out that product involvement is not constant for a product or type of product but varies for each customer (Koufaris et al., 2001-2002).

In the context of recommender systems, it can be assumed that consumers of different product involvement may require different information search need and explanation details given by the recommender systems. In this study, product involvement was set as a covariate to investigate its impact on persuasiveness of the recommendation as well as its possible interactions with types of recommender systems and product complexity.

Research Instrument

In this study, four dependent variables have to be measured. They are effectiveness, appropriateness, consistency, and persuasiveness. The persuasiveness and appropriateness scales used an existing scale in marketing, the persuasive disclosure inventory (PDI) for judgment of ads. According to McGuire (1969), the theoretical components of the PDI measures are ethos, pathos, and logos. Ethos refers to persuasive appeals that concentrate on the source rather than the message. Studies of advertising effects that have examined emotional or affective appeals fall within the definition of pathos. A logos appeal provides evidence or information about a concept from which a consumer can form beliefs (1994). Pathos and logos have been viewed by some as different ends of a continuum that considers the message. Feltham (1994) suggests that the subscales be used as individual message facets. The reliability estimates for the Pathos, Ethos, and Logos subscales were .83, .79, and .89 respectively. There is another persuasiveness scale developed by Keller and Block (Keller, and Block, 1997) to measure the effectiveness of a brochure to change the attitude of a person toward some topic. The topics focused on in the scales were health-related and the emphasis was on gauging the reader’s expressed intention to comply with the behavior suggested in the brochure. The scale had a high reliability (0.84) but no examination of the validity was reported by Keller and Block (1997). Compared to McGuires PDI, the brochure persuasiveness scale lacks face validity. The logos items were used to measure appropriateness and the ethos and pathos items were used to measure persuasiveness.

The scale for effectiveness used was the sales presentation effectiveness measurement developed by Behrman and Perreault (1984). The original scale was a six-item, five-point Likert-type scale purporting to measure salespeople’s self-evaluation of the effectiveness of a sales presentation. Reliability testing by Strutton and Lumpkin (1994) revealed a Cronbach’s alpha of 0.8. Both discriminant and convergent validity were reported by Behrman and Perreault (1984). Strutton and Lumpkin (1994) also proved the unidimensionality of the underlying data using maximum likelihood confirmatory factor analysis.

The questions used for consistency was from a study by Morris (1994) where items were used to test whether the recommendations from different databases are consistent with a user’s existing knowledge. The wording of the questions was adapted to the Purdue Consistency Testing Questionnaire on web site concept consistency (Ozok, 1997).

Product complexity measurement used the five-item, five-point semantic differential summated ratings scale measuring the perceived complexity of a product developed by McCabe (1987). The scale has a reported reliability of 0.80.

A variety of involvement frameworks have been proposed to guide advertising research. Most of the frameworks focus on the effects of some form of situational involvement on advertising effectiveness measures, such as processing of ad content or attitude toward the ad. Those scales are classified according to type of involvement and object of involvement (Day, Stafford, and Camacho, 1995). In this study, the four-item, eight-point Likert-type summated product involvement scales by Zinkhan and Locander (1988) was used. The original scale was developed to measure the degree of involvement a consumer has with calculators. The scale showed a reliability of 0.9 in the study.

Data Analysis

Data analysis consists of three phases: 1) pretest of the research instrument, 2) data collection and assessment of its measurement properties, and 3) hypotheses testing. To ensure the instrument has both face and content validity, the initial questionnaire was pre-tested by a smaller sample from a different group of students. Appropriate changes were made in accordance with pre-test results. The instrument was then administered to the identified sample.

First, the validity and reliability of all scales used was tested using factor analysis. The next phase is to test the research hypotheses. MANCOVA procedures will be employed to guard against type I error. In addition, because four dependent variables (appropriateness, consistency, effectiveness, and appropriateness) in this study are conceptually related according to Reardon's persuasion theory, the MANCOVA procedure is more suitable for this type of analysis that controlled correlations among dependent variables (Bary, and Maxwell, 1985). Product involvement will be used as a covariate to study its impact on persuasiveness and possible interactions with other factors. For main factors, differences of means related to the hypotheses were tested for statistical significance if the main effects show statistical significance. Univariate ANOVA analysis was used to test the sub-hypotheses 1-3 and ANCOVA was used to test hypotheses 4a, 4b, and 4c.

Implications of the Research

Most previous research on recommender systems has focused on the statistical accuracy of the algorithms driving the systems, with little emphasis on interface issues and the user's perspective. Recently, studies have begun to focus on the end-user side of the issue. Researchers have examined the impact of transparency (Sinha *et al.*, 2002), explanation (Herlocker, Konstan, and Riedl, 2000; Schafer, Konstan, and Riedl, 1999a; Ye *et al.*, 1995), trust, category risk, consumer knowledge, and product complexity (Swaminathan, 2003) on acceptance of recommendations given by recommender systems and its further influence on electronic commerce and online shopping. The investigation of persuasiveness provides another perspective to understand the online recommender systems. The results can be used by vendors and users of online recommender systems to improve online recommendation targeting and to lead product searching into actual purchasing.

Studies have been conducted to compare recommendations from recommender systems with human recommendations (Sinha, and Swearingen, 2001) and other expert systems (Morris, 1994). No research has been done to compare two recommender systems. Although there have been many algorithms used in recommender systems, collaborative-filtering and content-filtering are the two major types of algorithms that can be easily noticed by online consumers. The outcome of the research can help online vendors gauge and combine different algorithms for products of different complexity for better recommendation acceptance. Recommender systems can play the role of virtual advice-giving salespersons in an online context.

The use of persuasiveness theory brought in new insight to the end-user computing research in information systems. The Technology Acceptance Model (TAM) has been widely used to study different kinds of systems with additional constructs added. The persuasiveness theory is an alternative and concise model that can help explain the factors affecting the behavior of potential customers.

Product involvement is a well-researched factor in advertising study and has been investigated for its impact on web-based consumers. The introduction of this construct in the information system related research will provide a new application for this marketing concept and can bring novice understandings of the e-commerce related systems from a consumer's perspective.

Finally, the design of the research offered a within-subject design technique which is common in other disciplines but not so frequently used in information systems research. This method is highly sensitive in detecting statistically significant differences and allow for the use of much smaller sample sizes than necessary for between-subject designs (Cozby, 1989). Similarly, research in information systems tends to focus on development of new measurement scales for each study, to increase the validity of the instrument. The reuse of established scales tends to be neglected (Straub, 1989). This is contrary to the scientific principle of validation through repeated studies with the same instrument, and necessitates the use of large sample sizes as a diverse sample frame for each study. As a result, some worthwhile studies may not be performed due to the inability to secure large enough samples for the study.

The limitations of this study include the use of student samples, validity of scales, the carryover effect in the experiment design, and the use of existing recommender systems. Details will be given in the later discussion and summary chapter.

Items used in the questionnaire are listed in Appendix A.

Organization of the Study

This dissertation is organized into five chapters with appendixes. Chapter I provides an overview of the concepts of electronic commerce, decision support systems, intelligent agent, recommender systems, and persuasiveness theory. The research problems, significance of the research, research methodology, research contribution, and research implications are also included in this chapter. Chapter II provides an overview of the research relevant to persuasiveness, electronic commerce issues, factors impacting recommendation persuasiveness, and the research hypotheses for this study. Chapter III explains the methodology for sample selection, statistical procedures, and data analysis. Chapter IV presents the data analysis and results. Chapter V presents a summary of research findings, implications of the study, and directions for future research.

CHAPTER II

RECOMMENDER SYSTEMS AND HYPOTHESES DEVELOPMENT

This chapter presents a review of the research that comprises the theoretical basis for the current study. The chapter is divided into three parts: 1) an overview of the relevant research about the evolution of recommender systems in e-commerce, 2) a summary of the research about persuasiveness, and 3) the product complexity factor that is relevant to this study.

Recommender Systems in E-commerce

One of the earliest definitions of electronic commerce states that electronic commerce is a new way of conducting business characterized by companies and their customers performing electronic transactions through computer networks (Cronin, 1994). Based on this definition, technologies including Electronic Data Interchange (EDI), Electronic File Transfer (EFT), E-mail, facsimile (FAX), bar coding symbol technology, and enterprise messaging and file transfer have been linked to the development of electronic commerce within the business sector (Pyle, 1996). Yet it was not until the growing commercial use of the Internet, particularly the web subset of ITCP/IP, an interest in the benefit of conducting business electronically developed (Zwass, 1996). In this chapter, the focus is on the narrower definition of e-commerce, especially the commercial activities conducted over the Internet (Hake, 1999). Electronic commerce offers opportunities for businesses to make faster, cheaper, more personalized and more flexible ways to interact with both customers and suppliers. According to the nature of its transactions, e-commerce can be categorised into the following types: business-to-business(B2B), business-to-consumer(B2C), consumer-to-consumer(C2C), consumer-to-business(C2B), nonbusiness ecommerce (use of the Internet by nonbusiness organizations such as academic institutions or government agencies to reduce expenses or improve services), and intrabusiness e-commerce (Turban, Lee, King, and Chung, 2004). Currently, most recommender systems are either B2C or B2B. B2C will be the focus of this study.

B2C mainly refers to online retailing transactions with individual customers, where shoppers can conduct transactions through the webpage of a company. B2C e-commerce is becoming more widespread as more people are recognizing its convenience and capability to offer quick responses to requests as more products/services become available (Murch, and Johnson, 1999). He et al. (2003) stated that recommender systems can act as mediators in five of the stages of the consumer buying behavior (CBB) model. These stages are:1) need identification, 2) product brokering, 3) buyer coalition formation, 4) merchant brokering and 5) negotiation. This study will discuss the product brokering mediated by recommender systems where the systems assist the user about what product to buy to satisfy his or her need for some product or service.

He et al. (2003) divided e-commerce systems into two generations. In the first generation, buyers are generally humans who typically browse through a catalog of well-defined commodities (e.g., flights, books, computer components) and make fixed price purchases (often by credit card). The second generation e-commerce systems have a greater degree of automation on both the buyer's and the seller's side. Commerce becomes much more dynamic, personalized, and context sensitive in the context of web-based transactions. These changes can be of benefit to both the buyers and the sellers. From the buyers' perspective, it is desirable to have software that could search all the available outlets to find the most suitable one for purchasing the chosen good (e.g., the one that offers the cheapest price, the highest quality, or the fastest delivery time) and that could then go through the process of actually purchasing the good, paying for it, and arranging delivery at an appropriate time. From the sellers' perspective, it is desirable to have software that could vary its offering depending on the customer it is dealing with, what its competitors are doing, and the current state of its business. For example, the software agent can offer discounts or special offers to particular target groups. It can continuously monitor competitiors's prices and make sure its own price is competitive. The software agent can also reduce the product price to try and increase demand if the store has plenty of a particular item in stock.

Software agents like recommender systems distinguish the second generation of e-commerce applications. According to Shafer et al. (1999b), recommender systems can enhance e-commerce sales in three ways: 1) converting browsers into buyers, 2) increasing cross-sell, and 3) building loyalty. Recommender systems can help consumers find products they wish to purchase instead of pure searching. Additional products suggested during the search process could increase the average order size. Recommender systems improve loyalty by creating a value-added relationship between the site and the customer. When sites invest in learning customers using recommender systems to match customer need, consumers repay these sites by returning to the ones that best match their need. The more a customer uses the recommender system by teaching it what he wants, the more loyal he or she is to the site. Gaining customer loyalty is an essential business strategy where a site's competitors are only a click or two away (Reichheld, 1993; Reichheld, and Sasser, 1990).

Characteristics of Recommender Systems

Because recommender systems are software agents that can use behavioral or preference information to filter alternatives and make suggestions to a user (Ansari et al., 2000), it should have the basic characteristics of an intelligent agent. That is the capability of flexible autonomous actions to meet its design objectives. To achieve this, the software must exhibit these properties: reactivity, pro-activeness, autonomy, and social ability (Ansari et al., 2000; He et al., 2003).

Reactivity is the capability to respond appropriately to the prevailing circumstances in dynamic and unpredicted environments (Wooldridge, and Jennings, 1995). In other words, the recommender systems should be able to perceive and respond in a timely fashion to changes that occur in their environment in order to satisfy their design objectives. Pro-activity refers to the ability to act in anticipation of future goals so that the objectives of the owner are met. This way, when the environment changes, recommender systems can recognize opportunities and take the initiative if they are to produce meaningful results. The challenge to the agent designer is to effectively integrate goal-directed and reactive behavior (Rudowsky, 2004). Autonomy means the recommender systems must be able to make decisions about what actions to take without constantly referring back to their users (He et al., 2003). Sociability refers to the ability to interact with other agents or humans through negotiation and cooperation to satisfy design objectives (Rudowsky, 2004)

Approaches Used in Recommender Systems

Many different approaches have been used to solve the basic problems of making accurate and efficient recommender systems. Many of the technologies used in the recommender systems studied are fairly simple database queries. Automatic recommender systems, however, use a wide range of techniques, ranging from nearest neighbor algorithms to Bayesian analysis. The worst-case performance of many of these algorithms is known to be poor. However, many of the algorithms have been tuned to use heuristics that are particularly efficient on the types of data that occur in practice (Schafer et al., 1999b).

The earliest recommenders used nearest-neighbor collaborative filtering algorithms (Resnick, Iacovou, Suchak, Bergstrom, and Riedl, 1994; Schafer *et al.*, 1999b; Shardanand, and Maes, 1995). Nearest neighbor algorithms are based on computing the distance between consumers based on their preference history. Predictions of how much a consumer will like a product are computed by taking the weighted average of the opinions of a set of nearest neighbors for that product. Neighbors who have expressed no opinion on the product in question are ignored. Opinions should be scaled to adjust for differences in rating tendencies between users (Herlocker, Konstan, Borchers, and Riedl, 1999). Nearest neighbor algorithms have the advantage of being able to rapidly incorporate the most up-to-date information, but the search for neighbors is slow in large databases. Practical algorithms use heuristics to search for good neighbors and may use opportunistic sampling when faced with very large populations.

Bayesian networks create a model based on a training set with a decision tree at each node and edges representing consumer information. The model can be built off-line over a matter of hours or days. The resulting model is very small, very fast, and essentially as accurate as nearest neighbor methods (Breese, Heckerman, and Kadie, 1998). Bayesian networks may prove practical for environments in which knowledge of consumer preferences changes slowly with respect to the time needed to build the model, but are not suitable for environments in which consumer preference models must be updated rapidly or frequently (Schafer et al., 1999b).

Clustering techniques work by identifying groups of consumers who appear to have similar preferences. Once the clusters are created, predictions for an individual can be made by averaging the opinions of the other consumers in that cluster. Some clustering techniques represent each consumer with partial participation in several clusters. The prediction is then an average across the clusters, weighted by degree of participation. Clustering techniques usually produce less-personal recommendations than other methods, and in some cases, the clusters have worse accuracy than nearest neighbor algorithms (Breese et al., 1998). Once the clustering is complete, however, performance can be very good, since the size of the group that must be analyzed is much smaller. Clustering techniques can also be applied as a “first step” for shrinking the candidate set in a nearest neighbor algorithm or for distributing nearest-neighbor computation across several recommender engines. While dividing the population into clusters may hurt the accuracy or recommendations to users near the fringes of their assigned cluster, pre-clustering may be a worthwhile trade-off between accuracy and throughput (Schafer et al., 1999b).

Information filtering and information retrieval involve selecting text items that a user may be interested in reading based on the presence or absence of keywords in the text items. The users can explicitly enter the keywords, or the keywords can be inferred from the items that users have found interesting in the past. Information filtering or information retrieval systems are often used in search systems on e-commerce sites to help consumers find specific products in which they are interested (Schafer et al., 1999b). These systems have some features in common with recommender systems in that both systems produce lists of suggestions for a user. However, the more the system provides direct responses to syntactic user queries the less it feels like a recommender system to the user. Information filtering systems that notify users when interesting items are for sale are more like recommender systems, especially if part of the selection process involves attributes that are not under direct control of the user, such as whether other users have liked the item.

Classifiers are general computational models for assigning a category to an input. The inputs may be vectors of features for the items being classified or data about relationships among the items. The categories are a domain-specific classification such as malignant/benign for tumor classification, approve/reject for credit requests, or intruder/authorized for security checks. One way to build a recommender system using a classifier is to use information about a product and a customer as the input and to have the output category represent how strongly to recommend the product to the customer. Classifiers may be implemented using many different machine-learning strategies including rule induction, neural networks, and Bayesian networks. In each case, the classifier is trained using a training set in which ground truth classifications are available. It can then be applied to classify new items for which the ground truth is not available. If subsequent ground truths become available, the classifier may be retrained over time (Schafer et al., 1999b).

Classifiers have been quite successful in a variety of domains ranging from the identification of fraud and credit risks in financial transactions to medical diagnosis to intrusion detection. Basu et al.(1998) built a hybrid implementation induction-learned feature-vector classification of movies and compared the classification with nearest-neighbor recommendation. They found that the classifiers did not perform as well as nearest neighbor, but combining the two added values over nearest-neighbor alone.

Association rules have been used for many years in merchandising, both to analyze patterns of preference across products and to recommend products to consumers based on other products they have selected. An association rule expresses the relationship that one product is often purchased along with other products. The number of possible association rules grows exponentially with the number of products in a rule, but constraints on confidence and support, combined with algorithms that build association rules with itemsets of n items from rules with n-1 itemsets, reduce the effective search space. Association rules can form a very compact representation of preference data that may improve efficiency of storage as well as performance. They are more commonly used for larger populations rather than for individual consumers, and they, like other learning methods that first build and then apply models, are less suitable for applications where knowledge of preferences changes rapidly. Association rules have been particularly successful in broad applications such as shelf layout in retail stores. By contrast, recommender systems based on nearest neighbor techniques are easier to implement for personal recommendation in a domain where consumer opinions are frequently added, such as online retail (Schafer et al., 1999b).

Horting is a graph-based technique in which nodes are consumers, and edges between nodes indicate the degree of similarity between two consumers (Wolf, Aggarwal, Wu, and Yu, 1999). Predictions are produced by walking the graph to nearby nodes and combining the opinions of the nearby users. Horting differs from collaborative filtering as the graph may be walked through other consumers who have not rated the product in question, thus exploring transitive relationships that traditional CF algorithms do not consider.

Most of the online stores consider the algorithms they use to be proprietary. Individual recommender systems may actually use a combination of these algorithms while still presenting the same interface to the user. For this reason, this study concentrates on the two types of recommender systems that require different consumer input at the interface instead of the specific technologies used.

Types of Product Brokering Recommender Systems

To be able to make recommendations, the recommender system needs information from five information sources: 1) expressed preferences or choices of a person among alternative products, 2) preferences for product attributes, 3) preferences or choices of other people, 4) expert judgments, and 5) individual characteristics that may predict preferences (Ansari et al., 2000). A good recommender system should be able to use any or all of these five types of information to make better recommendations.

Based on the type of information needed and the presentation to consumers, recommender systems have been classified into three types. Those are the need-based/rule-based filtering, collaborative filtering and constraint-based/attributes-based/feature-based filtering (Ansari et al., 2000; He et al., 2003; Maes et al., 1999).

Need-based filtering identifies the needs of a customer (i.e. the intended use of a product, item location, the price range or the date limit and so on) and then recommends a product that meets those needs. Such a recommender system is expertise-driven, because a set of rules serve to interpret the specific information or intentions of the customer into a recommendation product configuration (Grenci *et al.*, 2002). The focus in need-based filtering is on the customer's intended use of a product, assuming the customer already knows the intended use of the product. This need-based filtering is also termed as rule-based filtering (Maes et al., 1999). For example, eBay guides a user to select the products by narrowing down the range of the possibilities based on the constraints the user gives and provides a list of the desired products that satisfy the constraints given by the user.

Collaborative filtering identifies how customers are grouped together with like-minded people, and explains that the product recommendations are based on the opinions of such people, assuming that they would like to buy similar products. Collaborative filtering predicts preferences of a person as a weighted sum of other people's preferences, in which the weights are proportional to correlations over a common set of items evaluated by two people (Ansari et al., 2000). For example, in CDNOW (www.cdnow.com), users are notified about the CDs or movies that are popular with other users with similar preferences.

Collaborative filtering algorithms have several limitations. First, when data are sparse, the correlations (weights) are based on few common items and therefore are unreliable. Second, collaborative filtering algorithms can be used only when preference data for an item already exists in the database. In other words, the system cannot handle queries about new items. Third, these methods use ad hoc prediction algorithms, which are not based on statistical models. Therefore, the uncertainty of the recommendation is high. This may be less important for low-risk purchases such as movies and compact discs but can be very important when the stakes are higher for a consumer or company. Fourth, collaborative filtering systems do not explicitly incorporate attribute information, though they are bootstrapped by creating “virtual users” who represent particular tastes. Finally, collaborative filtering methods are correlational. This feature provides little explanation for a recommendation and can be important for building trust and enhancing customer loyalty (Desharnais *et al.*, 2002; Wang *et al.*, 2003).

Attribute-based filtering recommender systems allow recommendations by first asking customers about their preferred levels of certain product attributes because these attributes are critical in product decision making as judged by the recommender systems based on their product expertise. Then, the system recommends a list of products that satisfy all customer hard constraints and is ordered by how well the products satisfy soft constraints. This allows recommendations for entirely new items but does not necessarily incorporate the information in preference similarity across individuals (Sarwar, Konstan, Borchers, Herlocker, Miller, and Riedl, 1998; Shardanand *et al.*, 1995). Similar to collaborative filtering, attribute-based filtering cannot make recommendations for people who provide no preference information. Systems that use neural networks often have difficulty providing explanations for recommendations (Ansari et al., 2000). Table 2 shows a comparison of recommender systems using different filtering algorithms.

Different types of recommender systems can have different implicit or explicit explanations regarding their reasoning process (i.e., their different ways to generate product recommendations). These can lead to different levels of recommendation persuasiveness. Wang and Benbasat (2003) show that different types of explanations in recommender systems increase different trusting beliefs of the consumer to recommendation generated. Rashid (2002) found that learning techniques of recommender systems affect the user effort and prediction accuracy. Furthermore, recommender systems have not been used in high-risk decision-making because of a lack of transparency in recommendation generation.

Table 2. Comparison of Filtering Algorithms Used by Recommender Systems (He et al., 2003)

	Feature-based	Collaborative	Constraint-based
Users' needs	Known	Unknown	Some known
Input	Product feature	User profiles	Functionality
Interaction	Medium	Few	Medium
Output	Goods with required features	Suggestions of goods to buy	Goods with required functionality
Suitability	Most goods	Books, CDs, etc.	Most goods

Persuasion and the Acceptance-Consistency-Effectiveness (ACE) Model

In its most general definition, persuasion is the process of attempting to change the behavior, belief, or attitude of the persuadee(s) toward a persuader-preferred mode of action, belief, or attitude (Reardon, 1991). In the context of using recommender systems to automate or assist customer product decision making, the term *persuasive* refers to the extent to which customers are moved or influenced by the recommender systems' reasoning to a belief that the recommended product best fits their personal needs (Komiak *et al.*, 2004).

In this study, the ACE model is used to compare the persuasiveness of two different recommender systems for several reasons. First, the ACE persuasion model provides a perspective different from adoption and acceptance of recommendations generated by recommender systems in e-commerce. In management information system research, the topic of user beliefs and attitudes change has been studied extensively (Barki, and Hartwick, 1994; Baroudi, Olson, and Ives, 1986; Fishbein, and Ajzen, 1975; Ginzberg, 1981; Hartwick, and Barki, 1994; Pare, and Elam, 1995). Especially user satisfaction and perceived usefulness are believed to be important factors for system acceptance, adoption, and system use (Davis, 1989; Davis, 1993; Davis, Bagozzi, and Warshaaw, 1989; Galletta, and Lederer, 1989; Gatain, 1994; Igbaria, and Machman, 1990; Igbaria, Schiffman, and Wieckowski, 1994; Iivari, and Ervasti, 1994a; Ives, Olson, and Baroudi, 1983; Keil, Beranek, and Konsynski, 1995).

For recommender systems, users cannot prove the correctness of the recommendation (whether the delivered products satisfy consumer requirement and needs) before they receive the products. With the convenience of the Internet, customers can search multiple sites for recommendations at almost no cost. Therefore, user acceptance of a recommendation is not supported by the actual satisfaction but by user beliefs about the recommendation argumentation given by the recommender system. This indicates the persuasiveness of the system. Kottemann et al. (1994) show that redundant what-if help increases users' confidence in the decision, and Davis et al.(1994) point out that irrelevant information in an information system weakens performance but increases the user confidence in decision making. Similar results were reported by Aldag and Power (1986) and Will (1992).

Persuasiveness reflects the power of the recommender systems to convince the customer. Persuasion process is a complex activity involving the sources, the media, and the receiver. The customer confidence in the recommender system, the customer self-confidence in decisions, and the degree of discrepancy between the customer opinions and the advising system opinions are all related to the persuasive power of the system (Jiang et al., 2000). The three variables have been described as "the immediate psychological determinants of belief change" (Jaccard, 1981). From the stand point of a recommender system, the source is the recommender system, the message is the recommendation, and the receiver is the consumer. The objective of a recommender system is to display recommendations to consumers and thus support and influence their final decision. Persuasion theory can be used to examine the persuasiveness of recommendations from different recommender systems.

The second reason for using the ACE model is its focus on recommendation messages rather than the consumer decision making process (Reardon, 1991). There are many factors affecting the persuasiveness of a recommendation from a recommender system. The study of persuasion processes should investigate all the elements of the communication process: source (e.g., expertise, trustworthiness, sex), message (e.g., tone, discrepancy, order effects, fear appeals, argument quality), and audience (e.g., self-esteem, intelligence, cognitive complexity, self-efficacy, perceived difficulty) (Areni, Ferrell, and Wilcox, 2000; Fishbein *et al.*, 1975; Fishbein, Hennessy, Yzer, and Douglas, 2003; Yzer, Hennessy, and Fishbein, 2004). It would be impossible to identify and measure all of the potential relevant features of the recommender system, kinds/formats of recommendation, and types of users in a given study.

The ELM model focuses on how persuasive messages are received. It predicts the likelihood that the persuadee will attend to the persuasive appeal, attempt to access relevant associations and experiences from memory, scrutinize and evaluate the information in light of the associations drawn from memory, draw references about the merits of the arguments, and derive an attitude toward the recommendation (Petty, Kasmer, Haugtvedt, and Cacioppo, 1987). When elaboration is needed, a person is more likely to use the central route to persuasion. When elaboration is not critical, the peripheral route is preferred. There are a number of variables that might affect the likelihood of elaboration, and a variable can play different roles in different persuasion situations. When people are either unmotivated to evaluate or incapable of evaluating the true merits of the arguments presented, they base their judgments on simple cues.

A fairly large body of research in the consumer information-processing domain suggests that the persuasive impact of advertisements depends on the extent to which executional cues within the advertisement are compatible with consumers' likely elaboration of brand information in the advertisement. When advertisements target consumers who are high in motivation, ability, and opportunity, they are most effective when they contain rational executional cues that credibly demonstrate the benefits of the product compared with competitive offerings (Petty, Shumann, and Cacioppo, 1983). Such cues enable consumers to engage in issue-relevant thinking and evaluate the true merits of the brand. The potential pool of rational cues includes messages 1) ranging from factual to feeling based (Olney, Holbrook, and Batra, 1991; Stewart, 1999; Torson, and Page, 1988), 2) indicating how the product is different from competitive product offerings (Stewart, 1999), 3) demonstrating product superiority (Petty, and Cacioppo, 1984; Sewall, and Sarel, 1986), and 4) focusing on product (MacInnis, and Jaworski, 1989) attributes and benefits as opposed to the user (Maheswaran, and Sternthal, 1990; Malaviya, Kisielius, and Sternthal, 1996; Stewart, 1999). When consumers motivation, ability, and/or opportunity to process ad information are low, such consumer devotes limited effort to processing message content or lack of sufficient knowledge to interpret and understand attribute-based information. Prior research has shown that under these low-elaboration likelihood conditions, cues such as expert endorsers, similar endorsers, and attractive pictures enhanced persuasion. These cues include affectively based cues and Heuristic cues.

Affectively based cues include likeable sources (Chaiken, 1980; Kahle, and Homer, 1985; Petty, and Cacioppo, 1981; Petty *et al.*, 1983), drama (Deighton, Romer, and McQueen, 1989), warm appeal (Stayman, 1990), visually appealing pictures (Grossman, and Till, 1998; Mitchell, 1986; Mitchell, and Olson, 1981; Stewart, 1999), and likable music (Bierley, McSweeney, and Vannieuwlerk, 1985; Gorn, 1982; MacInnis, and Park, 1991). Prior research has found that such cues can induce positive feelings in viewers and positively influence ad and brand attitudes.

Heuristic cues are shortcuts that enable inferences about brand benefits or quality. For example, although consumers may be unable to discern whether a brand is of high quality, they may come to believe it is when it is advertised by a credible source (Craig, and McCann, 1978; Sternthal, Dholakia, and Leavitt, 1978), or someone knowledgeable about the product category (Chaiken, and Maheswaran, 1994; Yalch, and Yalch, 1984). Although consumers may be unable to diagnose technical features of the brand made in ad claims, they may make inferences about its benefits from such easily processed persuasion cues as ad-relevant pictures (Kahle *et al.*, 1985; Miniard, Bhatla, Lord, Dickson, and Unnava, 1991; Mitchell *et al.*, 1981) or relevant music.

Although the ELM has gained considerable recognition, its application has been limited. Because the theory groups diverse processes (e.g., more coginitively based heuristic persuasion evoked from heuristic cues versus affectively based processing evoked from affective cues) under the general "peripheral" routes to persuasion. It is possible that various conditions dictate when certain types of peripheral cues are more effective than others.

Anderson's (1971) information integration theory has been applied largely to persuasion situations by including factors involved in the persuasion process. According to Anderson, the response of an individual on a scale after a persuasive message is a weighted additive function of the premessage belief of the individual and the position of the source of the communication. It can be expressed mathematically as $R= W_0S_0 + W_1S_1$ where R = the belief of the person after being exposed to the message, S_0 = the “scale value” of initial opinion of the person, S_1= the scale value of the source position, and W_0 and W_1= weighting parameters reflecting the psychological importance of the initial belief of the individual and the source position. The biggest challenge of this model is the difficulties in determining estimates of W_i and S_i.

It is understood that the study of persuasion process is an arduous task. People do not always reason about the information they receive (Petty et al., 1987). Petty et al. (1987) found that it is neither adaptive nor possible for people to exert considerable mental effort in processing all of the persuasive communication to which they are exposed. When motivation and ability to scrutinize information are low, it is still possible for people to form a new attitude or change an old one, but they do so through simple association, inferences, or heuristics rather than exerting the mental effort involved in reasoning about alternatives.

Research found that users sometimes accept expert system advice without going through thorough examination of correctness or the application of a cognitively convincing argument. They are likely to make their judgment on peripheral cues if they are less motivated or unable to judge a message on its contents (Petty *et al.*, 1986). Others simply want to reduce the cognitive effort by accepting advice of an expert system, even when they do not like it (Todd, and Benbasat, 1992).

This can be supported by more general research on decision making. According to Shugan (1980), the amount of thought that a human decision maker devotes to making a particular choice depends largely on the degree of decision making difficulty. Thinking effort is positively related to both the complexity of the decision and the desired level of confidence in having made the best possible choice. It is inversely related to the difference in the decision maker preference between the available options. As a result, complex and important decisions are more costly in terms of cognitive effort than simple and routine decisions. Individuals often settle for less accurate decisions in return for reduction in effort (Buttman, Johnson, and Payne, 1990). This is particularly true when alternatives are numerous or difficult to compare (Payne, Bettman, and Johnson, 1993). The use of decision support may result in effort savings but not improved decision performance (Todd *et al.*, 1992). Because feedback on effort expenditure tends to be immediate while feedback on accuracy is subject to delay and ambiguity, decision makers may be inclined to focus more on reducing cognitive effort than on improving decision accuracy (Einhorn, and Hogarth, 1978; Kleinmuntz, and Shchkade, 1993). The online vendors have virtually unlimited shelf space and can, therefore, offer a very large number of products to their customers. As a result, a potentially vast amount of information about market offerings is available to consumers. Searching through a marketplace composed of many such retailers would require consumers wishing to make well-informed decisions to expend a great deal of effort.

The ACE model deals with those situations where people are motivated to reason and are capable of reasoning about the alternatives presented in a persuasive message. It proposes that people tend to use three criteria to determine whether or not they should respond favorably to the arguments of a persuader: appropriateness, consistency, and effectiveness. In the context of this study, appropriateness refers to the extent to which the recommendation is approved by important others or whether it is based on rules, norms, etc. Consistency refers to the extent to which the products recommended by a recommender system are what the individual customers or other like-minded customers would own or purchase. Effectiveness refers to the extent to which a product recommended by a recommender system leads to desired ends of the customer (Reardon, 1991).

The ACE model is a framework providing insight into how messages might be developed to evoke liking/interest and comprehension through simple association, inferences, or heuristics in reasoning about alternatives (Reardon, 1991). These three criteria can be used by the persuaders to encourage one form of behavior over another by formulating strategies to show how the persuader-recommended behavior favorably responds to those considerations.

Product Complexity

In an online shopping context, the perceived complexity of a product refers to the quantity and quality of information associated with the number of product attributes and the number of alternatives available.

Various studies have investigated the impact of product complexity on decision-making. Bettman et al. (1998) argued that the consumer decision making processes are related to the complexity of the product in a product category. He suggested that as the complexity of the product increases, consumers are likely to resort to simpler heuristics and selective information processing, often reducing decision effectiveness. Keller and Staelin (1987) showed that as the number of attributes and alternatives increase, the decision effectiveness is reduced. Payne et al. (1993) suggested that an increased number of alternatives may result in greater cognitive load and create biases in consumer decision-making processes.

The product complexity can cause subjective information overload experience in the consumers. They would have difficulties in identifying the relevant information (Jacob, 1977), become highly selective and ignores a large amount of information (Bawden, 2001; Herbig, and Kramer, 1994), need more time to reach a decision (Jacob, 1984), and finally do not reach a decision of adequate accuracy (Malhotra, 1982). Intelligent information management systems such as recommender systems can prioritize information (Bawden, 2001; Meyer, 1998) and provide quality filter (Edmunds, and Morris, 2000; Grise, and Guallupe, 1999/2000) so that a large set of options can be reduced to a manageable size (Cook, 1993).

The recommender system organizes the product information in such a manner that the consumer is able to focus on those attributes that are most likely to maximize utility. Therefore, the impact of using a recommender system on decision-making is likely to be the greatest in a highly complex category where consumers often resort to decision making heuristics to manage the information overload.

Research Hypotheses

Studies of persuasiveness of recommender systems and other expert systems have focused on the factors influencing the end user confidence in the decision support provided by the system. Those factors include trust, explanation, transparency, and learning techniques of the recommender system. Wang and Benbasat (2004) found out that different types of explanation in recommender systems increase different trusting beliefs. The initial trust of customers can directly affect their intention to adopt the recommender system and indirectly enhance their perceived usefulness of the system. Explanation shows the reasoning process and can convince decision makers of the recommendation soundness (Ye *et al.*, 1995) because decision makers tend to discard recommendations that they do not fully understand if they will be held responsible for their decision (Hollnagel, 1987). Recommender systems have not been used in high-risk decision making for lack of transparency because it is difficult for the system to demonstrate how the decisions are reached (Herlocker *et al.*, 1999; Sinha *et al.*, 2002).

As has been discussed earlier, recommender systems use different information and algorithms in the reasoning process. They vary by 1) how much the consumers can and are willing to input, 2) the explanation capability of the algorithm, 3) what products are involved, and 4) the availability of the reference information (Ansari et al., 2000). Studies have compared recommender systems with human recommendation (Sinha *et al.*, 2001).

In this study, the ACE model of persuasion (Reardon, 1991) is used to compare the persuasiveness of the two different recommender systems. The research model is presented in Figure 2.

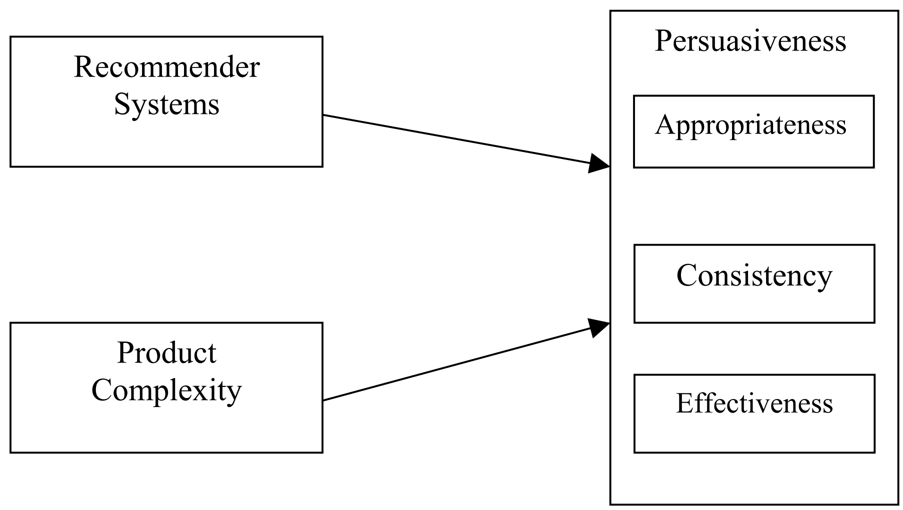

Figure 4. Research Model

Appropriateness refers to the extent to which the recommendation is approved by important others or whether it is based on rules, norms, etc. Recommendations from both types of recommender systems are the result of its internal reasoning by either product expert or customer expert. The reasoning is based on pre-set rules. However, content-based filtering recommender systems appear to provide recommendations that are higher on the appropriateness dimension because the reasoning logic of content-based recommender systems makes the recommended products more likely to be the right products than do the reasoning logics of collaborative-filtering recommender systems.

Although collaborative filtering recommender systems are given ratings of a list of product to compare with other people's choice, a particular customer may wonder how similar those like-minded people are to him/her. Furthermore, the reasoning logic of content-based filtering recommender systems is more transparent and easily understood by customers.

Consistency refers to the extent to which the products recommended by a recommender system are what the individual customers or other like-minded customers would own or purchase. Consistency has been used as a measure for expert system acceptance (Morris, 1994) and marketing success (Chernatony, and Segal-Horn, 2003; Swait, and Erdem, 2002). Consistency involves both context and temporal dimensions. The recommendation should be consistent with the consumers' existing knowledge, which can be obtained by consumer rating of products or from preference of other like-minded people. Collaborative-filtering recommender systems appear to give product recommendations with higher consistency because they make recommendations based on like-minded customers' opinions, while content-based filtering do not consider the opinions of other like-minded customers.

Effectiveness refers to the extent to which a product recommended by a recommender system leads to the customers' desired ends. In this context, it could be argued that the usefulness of the product within the context of its intended use can be considered to be customers' desired end. It is expected that content-based filtering recommender systems will be perceived to be more effective than the recommendations by collaborative-filtering recommender systems because the former explicitly ties the recommendations to customers' desired ends, while the latter does not explicitly ask about customers' desired ends nor include their desires in its reasoning logic. Therefore,

H_1: Types of recommender systems influence recommendation persuasiveness.

H_{1a}: Content-based filtering recommender systems will be perceived to have a higher degree of appropriateness than the collaborative-filtering recommender systems.

H_{1b}: Collaborative-filtering recommender systems will be perceived to have a higher degree of consistency than content-based filtering recommender systems.

H_{1c}: Content-based filtering recommender systems will be perceived to have a higher degree of effectiveness than the collaborative-filtering recommender systems.

The benefit of using a recommender system is likely to be higher when the product complexity is greater (Swaminathan, 2003). When complexity of the product increases, consumers are likely to do selective information processing by concentrating on those attributes that are most likely to maximize utility in order to reduce the cognitive effort (Bettman et al., 1998).

$H_{2:}$ Product complexity influence recommendation persuasiveness.

H_{2a}: Product complexity influence recommendation appropriateness.

H_{2b}: Product complexity influence recommendation consistency.

H_{2c}: Product complexity influence recommendation effectiveness.

To test the possible interaction between product complexity and types of recommender systems, a third group of hypotheses is formed:

H_3: Product complexity interacts with types of recommender system in affecting recommendation persuasiveness.

H_{3a}: Product complexity interacts with types of recommender system in affecting recommendation appropriateness.

H_{3b}: Product complexity interacts with types of recommender system in affecting recommendation consistency.

H_{3c}: Product complexity interacts with types of recommender system in affecting recommendation effectiveness.

Based on Reardon's persuasion theory (Reardon, 1991), appropriateness, consistency, and effectiveness are three criteria that help consumers determine whether or not they should respond favorably to a persuader's argument when people are motivated to reason and are capable of reasoning about the alternatives presented in a persuasive message. Therefore, it is expected:

H_4: Recommendation appropriateness will be positively associated with the recommender systems' persuasiveness.

H_5: Recommendation consistency will be positively associated with the recommender systems' persuasiveness.

H_6: Recommendation effectiveness will be positively associated with the recommender systems' persuasiveness.

CHAPTER III

RESEARCH METHODOLOGY

The previous two chapters introduced the topic of the research, the review of the literature, and the hypotheses. This chapter covers the methodology used in this study. It includes the pilot study, research design explaining selection of research subjects, selection of products for experiment, selection of websites for recommender systems, the research instruments, the experiment procedure, and data analysis and statistical procedures. Much emphasis is given to the process of the research method. Based on the information gathered from the pilot study, a modified questionnaire for collecting data will be discussed.

Pilot Study

To ensure understanding of the experiment procedure instruction and survey questions by the research subjects, a convenience sample of 12 undergraduate students in MIS or business was used for a pilot test. The purpose of the pilot test is to confirm that all instructions, variables and their measurement scales are appropriate, correct, and understandable for the respondents. The feedback forms included open-ended questions to maximize the breadth of feedback and were returned anonymously. Modification of the experiment procedure instructions and survey questions was made based on the comments and recommendations.

Research Subjects

The experiments are aimed at online customers. After pilot testing the data collection instrument, a selected student sample from a junior-level Business Information System course at Mississippi State University was used for the experiment.

The adequacy of students as surrogates for non-students is a controversial issue in behavior research. Numerous studies of surrogacy have been conducted in different contexts, with mixed results. Some research studies question the external validity of results on the basis that students fail to represent non-students (Copeland, J., and Strawser, 1973; Gordon, Slade, and Schmitt, 1986; Miller, 1966; Sears, 1986). Stafford (1998) and Yavas (1994) found students to be poor surrogates of real-world consumers, since typical students often did not use the products being tested. Robinson *et al.* (1991) suggested that students and entrepreneurs differ on a variety of characteristics that are dynamic across time and situations. Others, however, argue that it is the subject's interpretation of the task and meanings they attribute that affect the external validity more than the subject type (Berkowitz, and Donnerstein, 1982). Some have found students to be adequate surrogates for real-world decision makers. For example, simulation studies that examined marketing and advertising issues have revealed no difference between managers and students (Kuehn, Khandekar, and Scott, 1996; Waters, and Collins, 1984). In an inventory management context, Mowen and Mowen (1986) found that both students and managers exhibited the same pattern of decision bias due to the way the information was framed.

Findings from different decision contexts suggest that the adequacy of student surrogates depends on the type of decision being investigated, perhaps because different decisions require different types of experience and expertise (Chang, and Ho, 2004). Lock (1986) indicates that findings of laboratory experiments can be generalized to field settings, despite the differences in subjects, tasks, and settings. He suggests that the available evidence suggest that experimental realism has a better chance of generalizing the results to other situations, settings, or people than the superficial similarity of representativeness. Therefore, even though the student sample is not representative of the overall population, and their responses may not be generalizable, students should provide adequate opinions for this exploratory study, particularly as they represent substantial online purchasing power and generally have some experience with web surfing.

Selection of Products for Experiments

Two products of different product complexity were used as the test products in this study. A variety of products have been used to study recommender systems. They include the backpacking tent and compact stereo (Haubl *et al.*, 2000), digital camera (Wang *et al.*, 2004), movie (Ansari et al., 2000; Herlocker et al., 2000), CD writer and golf club (Yoon, and Lee, 2004), tent and toothbrush (Swaminathan, 2003), and books (Sinha *et al.*, 2001). It has been suggested that when using recommender systems for product searches, collaborative filtering is more specialized than content filtering because it works based on perceived quality and tastes of people rather than objective properties (Shardanand *et al.*, 1995). Thus, recommender systems using collaborative filtering are more suited to experience goods such as books, CDs, and movies because subjective judgment that acts as the differentiator in these cases. Most of the previous studies about collaborative filtering used CDs, books and movies because of the limitation of collaborating algorithms used. Amazon.com is the company that introduced collaborative filtering to a wider number of items and people in 1998. The company's goal is to offer "something for everybody" using the online recommender system.

In order to select two products that rated high and low on product complexity, a pretest with the 14 product categories from the website using the content-based filtering recommender system (www.activebuyersguide.com) was evaluated in a focus group of 15 participants to find the two products. The website is chosen because the collaborative filtering site has much broader product categories that cover all the categories in this site. The 15 participants in the focus group were similar to the target sample. They were asked to brainstorm for products from the list that are relevant to the target population, have broad market appeal, and could be bought online. The chosen number of products was tested in a group of 30 using the 5-item, 5-point semantic differential scale for product complexity (McCabe, 1987). The resultant products with highest complexity (notebook computer) and lowest complexity (DVD player) were used in the experiment for persuasiveness study.

Selection of Websites for Recommender Systems

In order to eliminate potential confusion from complicated shopping sites and to simplify the experiment related to different recommender systems, two websites were selected. The website for collaborative-filtering recommender system is www.amazon.com. The one for content filtering recommender system is www.activebuyersguide.com.

Although there were several commercial websites using collaborative-filtering recommender systems (i.e. www.firefly.com, www.shopping.com, and duuni.talentum.com), many of them have closed down. Amazon.com is the most successful and comprehensive one that still exits and has been used by many in collaborative filtering recommender systems research (Komiak *et al.*, 2004; Schafer *et al.*, 1999b; Sinha *et al.*, 2001; Sinha *et al.*, 2002). The online recommender systems can provide product recommendations based on a consumer's past purchase if it is a return customer. For new customers, they are first asked to rate a list of products they own or like, then the system compares the consumer's product ratings with those of other consumers. After identifying the consumer's nearest neighbors, the system recommends products that neighbors have rated highly but which the shopper may not yet have rated.

The active sales assistant site (www.activebuyersguide.com) uses content filtering recommender systems that allow consumer input of multiple product attributes (i.e. price, brand, specific functionalities, warranty, and accessories) to locate the merchant that satisfies their needs. Like most real-world content-based filtering recommender systems, it only considers a subset of all the relevant attributes in a product category. The reasons for this selectivity as stated by Haubl and Trifts (2000) include (1) the large number of attributes that exist in many product categories, (2) the substantial amount of data about a consumer that would be required to develop an accurate understanding of the consumer's subjective preferences, (3) an inclination to use only those attributes that are common to most or all available products, (4) a tendency to include only attributes that are quantitative in nature, and (5) a strategy to emphasize or de-emphasize specific attributes.

Most of the prior studies used self-built recommender systems instead of existing commercial applications to control the initial trust or website credibility factors. There are several reasons for using two existing websites in this study.

First, prior studies do not make comparisons of different recommender systems. Most of them focus on the impact on consumer decision making with vs. without the recommender system (Desharnais *et al.*, 2002; Haubl *et al.*, 2000). The recommender systems in real world applications are all embedded in websites. One way to get around this problem is to consider the whole website as the recommender system itself.

Second, some comparison studies did use existing commercial websites with recommender systems. Sinha and Swareingen (2001) compared social recommendation from friends to online recommender systems for movie and music search. They also used five existing music websites to compare the role of transparency in recommendations provided by different online recommender systems (Sinha *et al.*, 2002).

Finally, students were asked to use different email addresses for identification each time when searching the products using the collaborative filtering recommender system by following the recommendation wizard. Cookies in the computers was disabled. Therefore, every login is registered as a new customer. This eliminated the impact on system recommendation by existing consumer buying/browsing history during the experiment (Sinha *et al.*, 2001). As will be talked about in the experiment procedure section, within-subject design and counterbalanced question orders were used to alleviate the impact from the participants.

Research Design

The research design in this dissertation was a 2x2 within-subject factorial design. The manipulated factors are: recommender systems (collaborative filtering, content-based filtering) and product complexity (high, low). Product involvement was used as a covariate. Participants were asked to purchase two different products using each recommender system. That is, each participant tried the four experiment conditions of the 2x 2 within-subject sub-design. The total number of questionnaires was equally divided into 4 parts, each part with a different combination of product and recommender system sequence, and was administered to four groups of students. This necessitated a counterbalancing of products and recommender systems usage order. The within-subject design controls for participant difference.

As a result of this experimental design, the influence of recommender systems and product complexity could be measured reliably. All other factors related to the consumer, such as emotional disposition, cognitive complexity, expectations, schemata, and expressed preferences were controlled by the within-subject design. Since all these individual characteristics should not vary in different situations, no hypotheses for them were formulated. The product involvement was used as a covariate to control an important kind of extraneous variance.

The within-subject factorial design is also called a repeated measure design. It is used when the characteristics of the participants are correlated with the dependent variable and will influence the result (Cozby, 1989). In a within-subject design, all participants receive all levels of independent variable treatment.

An obvious advantage of within-subjects design is that fewer subjects are needed, because each subject participates in all conditions. This design is preferred when subjects are scarce or when it is costly to use subjects. An additional advantage of within-subject design is that they are extremely sensitive to finding differences between groups. Because subjects in the various groups are identical in every respect (they are the same people), error variability due to subject differences is minimized (Cozby, 1989). By using counter-balancing, the unexplained variability in the result can be more readily identified, which results in a more sensitive statistical test. It is more likely to detect an effect of the independent variable if a within-subject design is used.

Two major concerns for within-subject design are the carryover effects and demand on participants. Participants need to be tested on all the treatment conditions. Therefore, fatigue becomes a greater concern. They may quickly figure out the true purpose of the experiment and behave differently than they would if they were unaware of the hypothesis. In this study, an open-ended question was used at the end of the questionnaire as a manipulation check to assess the students' awareness of the experiment purpose.

When exposed to the experiment stimulus more than once, the participants can learn how to perform the task, get tired, and change responsiveness. The learning or habituation caused can lead to a carryover effect. The carryover effect is also referred to as anchoring (Tversky, and Kahneman, 1974). When subjects are asked to give an estimate of a value for which they have little or no reference values, the first estimate will influence subsequent estimates. The tendency is to make a "reasonable adjustment" from the previous value(s). If the initial value is low, subsequent estimates tend to be at the lower end of the range. On the other hand, if the initial estimate is high, the subsequent estimates tend also to be at the higher end of the scale. The effect of basing repeated estimates on earlier figures has been described by Northcarft and Neale (1987), who asked the participants in their study to estimate real-estate values after hearing manipulated listing prices. The only influence on participant estimates was the magnitude of the listing price manipulation, whereas expertise and experience did not influence the participants estimates. Another example is the study of Block and Harper (1991), where point estimates could be influenced by being told the point estimate of another participant in the study.

The carryover effect can be minimized by counterbalancing. By arranging the various treatments in different orders for different participants, each treatment occurs in each time period of the experiment. In the end, everyone experiences the same treatments, just in different orders. If a previous measurement serves as an anchor and a "reasonable adjustment" is made, any deviation of the next measurement must be in the direction towards the previous measurement. In a series of measurements with the factor alternating, this serves to decrease the actual difference if any anchoring takes place. Statistically significant differences between groups depend on large enough differences of the means of the groups, given the sample size and the distribution within the groups. Anchoring can potentially decrease the difference between means. It does not influence the sample size and distribution in the group, since the group size is fixed and errors are assumed to be normally distributed. If the difference of means is statistically significant, and anchoring has had an effect, the real difference is even larger, and therefore always statistically significant.

Covariate

Product involvement was used to control for extraneous variation in the dependent variables. Covariate that is uncorrelated with the other independent variables but explains significant variance in the dependent variables helps remove predictable variance from the error term, thus increasing the power of the analysis (Tabachnick, and Fidell, 1983).

According to the advertising and marketing literature, product involvement is a factor that may influence consumers' cognitive and behavioral response to online advertising. It can affect consumers information search style, process motivation, and understanding of the message (Ahn *et al.*, 2002; Cho *et al.*, 1999; Karson *et al.*, 2001; Laczniak *et al.*, 1999; Yoo *et al.*, 2001). It also varies for each customer (Koufaris et al., 2001-2002). It is likely that product involvement will have an impact on the consumers' perception of the persuasiveness of the recommendation given by online recommender systems. Because the subject factors were controlled using the repeated measures design used in this study, product involvement was included as a covariate to investigate its possible influence on and interaction with other dependent variables.

Research Instrument

To ensure that the questions comprising the instrument were formally reviewed for content, clarity, and sequencing, two different groups of people performed a general review of the instrument. First, the questionnaire was reviewed for wording clarity and content validity by business faculty members and colleagues at Mississippi State University. Items were evaluated for ambiguity, construction faults, sequencing, and flow. Modifications were made to the instrument in accordance with their comments.

The instrument was then reviewed by the Mississippi State University Institutional Review Board for the Protection of Human Subjects. The objective of this review board is to ensure that the research being conducted by university faculty and students adheres to established research policies and procedures, and does not unnecessarily place the subjects used in the research effort at risk either mentally or physically.

Finally, the instrument was pre-tested using a convenience sample of 12 undergraduate students at Mississippi State University as mentioned in the pilot-study description. Modifications were made to the instrument in accordance with their comments prior to the formal experiment in the computer lab.

The research instrument in this study is comprised of four sections (Appendix A). The first section of the instrument is a cover letter explaining the purpose of the study. The second section contains definitions of key terms that are included in other sections of the instrument. Because definitions for these terms may vary based upon their use and reference in prior research, a baseline definition for each of these terms is necessary. These definitions are based on a synthesis of various definitions offered by other research.

The third section of the instrument includes items used to measure the four dependent variables and one covariate in this study. These are effectiveness, consistency, appropriateness, persuasiveness, and product involvement. Multi-item indicators was used to measure each. The items were measured using seven point Likert-type rating scales. Because of the lack of information systems persuasiveness studies, all of the measurement items were derived from previous marketing, psychology and information systems literature related to the individual construct. Twenty items were used to measure the four constructs included in this section. Table 3 describes the operationalization of each variable along with corresponding references.

Appropriateness was measured using five items that assess the respondent's perception of the fitness and desirability of recommendations given by the recommender system. The scale used is the logo items of the Persuasive Disclosure Inventory original to Feltham (1994). According to Feltham (1994), a logos appeal provides evidence or information about a concept from which a consumer can form beliefs. The 7-point scale has a reliability of 0.86 in the original study and 0.79 in a second verification study. One other scale, brand name appropriateness, is developed by Allen and Janiszewski (1989) who studied a subject's attitudinal evaluation of a specific brand name in constructing advertisement. In psychology, concern for the appropriateness scale is a 20-item measure of tendencies to conform to group conformity pressures. It has been used to investigate individual differences in susceptibility to peer pressure (Johnson, 1989), social anxiety (Lennox, and Wolfe, 1984), and ad context (Celuch, Slama, and Schaffenacker, 1997). This scale is not chosen for the study because the large number of items can make the data collection sessions too long and could contribute to respondent fatigue. The perception of the appropriateness of a recommendation given by an online recommender system is more like a personal evaluation of the marketing tool used by an online store. It is an individual decision with very little pressure from peers or society. The logos scale developed by Felthem was used because the brand name appropriateness is too specific for this study of recommendation appropriateness.

Consistency was measured using a scale developed by Morris (1994). The original scale includes functionality consistency and recommendation consistency, which are used to compare recommendations generated by different databases with the user's existing knowledge. Consistency has been studied heavily in marketing studies. Swait and Erdem (2002) suggest that sales promotion mix consistency can improve consumer brand evaluation. Burton et al. (1993) studied the effect of information consistency in advertisement on consumer reference-price predictions. Information consistency (i.e., all neutral information versus one piece of positive information about the product alternative) was manipulated by Meloy (1997) to assess the role of positive affect and mood maintenance on pre-decisional distortion of evaluations of product information in preferential choice. Jain (2003) used a two-item 9-point Likert-scale to measure preference consistency and found that people are less resistant to changing preference when processing preference-inconsistent information. The items in this scale measure generalized consistency perceived by respondents. This scale can even be used for abstract concepts, but not for a specific system recommendation because it might confuse the respondents due to its ambiguity. The final scale items used were reworded according to the Purdue Consistency Testing Questionnaire (Ozok, 2000) which measures the concept consistency for information and knowledge as a subdimmension of webpage evaluation.

Effectiveness, the perceived degree of recommender systems' capability to clearly understand and address the need and concerns of the respondents, was measured by six items. Although there are many scales developed for information systems effectiveness, most of them are about large information systems in the organizational setting and none of the effectiveness measurements addressed the question in an individualized style. User satisfaction and organizational change are the two most commonly used surrogates to measure effectiveness of information systems (Gatain, 1994; Iivari, and Ervasti, 1994b; Lee, and Kim, 1995; Miller, and Doyle, 1987; Yuthas, and Young, 1998). In this study, the sales presentation effectiveness scale was used. It is a six-item, five-point Liket-type scale and is intended to measure salespeople's self-evaluation of the effectiveness of a sales presentation. The recommendation from recommender systems can be considered as a sales agent for online retailers. By giving recommendations for products that fit the consumer taste or requirements, the recommender system can promote consumer inclination towards certain products, reduce consumer search effort, improve decision quality, and increase satisfaction and loyalty to the online store. The scale also emphases the fulfillment of individual needs rather than organizational or job-related goals.

Persuasiveness refers to the extent to which customers are influenced by the reasoning of recommender systems to a belief that the recommended products best fit their personal needs (Komiak *et al.*, 2004). It was measured using (Feltham, 1994) PDI scale. The original scale includes items for measuring pathos, ethos, and logos. It has been suggested that the subscales can be used as individual message facets (Feltham, 1994). In this study, only items for ethos and pathos were used because the pathos and logos have been viewed by some as different ends of a continuum that consider the message. There are 5 items for ethos and 7 items for logos. The sum scores across the items are used to reflect ethos and pathos respectively. The original within-factor item-to-total correlations were within the range of 0.63 to 0.91, with coefficient alpha estimates of 0.89 and 0.82 respectively (Feltham, 1994). A second validation study showed the average of item-to-total correlations as 0.78 and 0.79 for ethos and logos subscale while the average reliabilities were 0.83 and 0.89 respectively. The original scale items were bipolar adjective sets using a 7-place response format. To keep them consistent with the other scales used, the items used in the experiment were in the format of a 7-point Likert scale.

Product involvement was measured using the four-item, eight-point Likert-type summated product involvement scales by Zinkhan and Locander (1988). The original scale was developed to measure the degree of involvement a consumer has with calculators. The scale showed a reliability of 0.9 and 0.873 as reported by Zinkhan, Locander, and Leigh (1988) and Zinkhan and Locander (Zinkhan, and Leigh, 1986), respectively. Both studies found this measure multi-dimensional. Zinkhan, Locander, and Leigh (1986) used it to examine the dimensionality of several predictors of ad recall and recognition measures. Two dimensions were found, one more affective and the other more cognitive. Zinkhan and Locander (1988) used the technique to investigate four advertising recall measures and found that two dimensions were actually being measured: favorable recall of ad features and brand name recall.

Table 3. Operationalization of Research Variables

Variable	Operationalization	Sources	Cronbach's Coefficient Alpha
Appropriateness	Mean of 5 items	Feltham, 1994	0.89
Consistency	Mean of 5 items	Morris, 1994	n/a*
Effectiveness	Mean of 6 items	Behrman & Perreault, 1984	0.8
Persuasiveness	Mean of 12 items	Feltham, 1994	0.83/0.79
Product Involvement	Mean of 4 items	Zinkhan and Locander, 1988	0.90
Product Complexity	Mean of 5 items	McCabe, 1987	0.80

Note: * indicates that the coefficient alpha value was not calculated on that study.

The fourth section of the instrument contained general information about the respondents: their age, gender, major, level of computer usage experience, level of Internet usage experience, level of online recommender system usage experience, ethnicity, and whether the respondents would like to have a copy of the major findings from the study.

All scales were assessed for face validity, construct validity, and reliability. Details were described in data analysis and statistical procedures section.

Experiment Process

The experiment was conducted in the Seal computer lab located in the College of

Business and Industry at Mississippi State University. Seal contains 30 workstations connected through the Netware local area network. Each station is equipped with a Pentium microprocessor and has multimedia capacities.

The experiment was divided into four sessions with 30 participants each. To eliminate the order effect in repeated measures design, the questionnaires were randomized by latin square design by using each of the 4 orders of the four treatments (recommender system and product complexity combinations) for each of the four experiment sessions. Cozby (1989) suggested a minimum of about 30 participants per cell in repeated measures design. Therefore, a total of 120 usable questionnaires will be the minimum needed.

Each experiment session lasted about 40 minutes. The researcher asked the participants to sign the informed consent form and explained the purpose of the experiment in general terms. Students were asked to search for two products using two different online recommender systems. The detailed instructions for the experiment are available in Appendix A. Each student had approximately seven minutes to visit each online recommender system. When each web site visit was completed, the students were asked to answer the persuasiveness questions.

Repeated measures cannot be evaluated in a random design, because the assumption of independent errors is not met. Observations made by the same participant are not independent. However, the use of a randomized complete block design is appropriate, with participants as the blocking factor. Other factors pertaining to the consumer are included in participants as the blocking factor. The measurement model is:

$У_{ijk} = \mu + \alpha_i + \beta_j + (\alpha\ \beta)_{ij} + \delta_k + \varepsilon_{ijk}$,

where

α_i is a fixed factor for recommender system ($\Sigma\ \alpha_i$=0)

β_j is a fixed factor for product complexity ($\Sigma\ \beta_j$=0)

$\alpha\ \beta_{ij}$ is interaction between recommender system and product complexity

($\Sigma\ \alpha\ \beta_{ij} = 0$)

δ_k is a random factor for participant as block (δ_k~N $(0,\sigma^2)$, iid)

note: iid = independent and identically distributed

N $(0, \sigma^2)$ = Normal function with mean μ and variance σ^2

Data Analysis and Statistical Procedure

Face validity, construct validity and reliability were tested first. Face validity involves the systematic examination of the content of the instrument to determine whether the instrument provides adequate coverage of the problems or topics included in the study (Emory, and Cooper, 1991). An instrument is said to have a high level of face validity if it contains a representative sample of the universe of subject matter of interest. The face validity assessment procedure is a subjective process. Anastasi (1968) and Churchill (1979) suggest consulting experts who are considered knowledgeable on the research topic. One professor in marketing and two professors in MIS were asked to review the instrument.

Reliability is defined as the accuracy or precision of the research instrument and is calculated as a proportion of the true variance to the total variance yielded by the measuring instrument (Kerlinger, 1986). Reliability can also be defined as the degree to which measures are free from error and therefore yield consistent results (Peter, 1979). One aspect of reliability is internal consistency which is an indicator of the homogeneity of a measuring scale (Cronbach, 1951). One criteria that has been consistently used to assess the reliability of multi-item measurement scales is Cronbach's (1951) coefficient alpha. Nunnally (1978) suggested that a set of items with a coefficient alpha greater than or equal to 0.7 is considered to be internally consistent. However, reliability is a necessary, but not sufficient condition, for construct validity. Thus, those aspects of construct validity were examined.

Construct validity pertains to the overall degree of correspondence between the constructs and the measures used to represent the construct (Peter, 1981). One part of construct validity is unidimensionality of the sets of items used to measure a given construct. Unidimensionality is whether items measuring a construct measure only that construct (Walizer, and Wienir, 1978). One method used to assess the unidimensionality of items is exploratory factor analysis (Harmon, 1976).

Principle component factor analysis was used to assess each of the multi-item scales in the questionnaire. Dimensionality of each factor was assessed by examining the factor loadings. Items with factor loadings of greater than .50 on the factor with which they are hypothesized to load were considered adequate indicators of that factor.

Two additional aspects of construct validity are convergent and discriminant validity (Nunnally, 1978). Convergent validity is the extent to which a measure correlates highly with other methods designed to measure the same construct (Churchill, 1979). Principle component factor analysis was used to assess each factor for convergent validity. Factors with eigenvalues greater than 1.00 and factor loadings greater than .30 were considered to have adequate convergent validity (Caller, and Carmines, 1980).

Discriminant validity is determined by demonstrating that a measure does not highly correlate with another measure from which it should differ (Campbell, and Fiske, 1959). An examination of the cross-loadings of items on multiple factors was used to assess how well items discriminant between factors.

MANCOVA was used to evaluate hypotheses 1 to 3. Assumptions of this type of ANOVA include independence of the treatments (treatments do not influence each other), independence of the subjects, and homogeneity of variance. Within-subject measurement carries the risk of unequal variances between the subjects. Independence of the treatments was pursued by a deviation from complete randomization within the participant block, as will be explained in the next chapter. During the experiment, the researcher will request participants to not discuss anything about the study with others while the experiment is in progress. The relationship between the three ACE model constructs (appropriateness, consistency, and effectiveness) and persuasiveness as stated in hypotheses 4a, 4b, and 4c was examined using ANCOVA.

In conclusion, the research hypotheses were tested in an experimental design setting. Analysis was performed with MANCOVA for a repeated measures design for hypotheses 1-3, with recommender systems and product complexity as main effects and product involvement as a covariate. Hypotheses 4a, 4b, 4c were tested using ANCOVA. The next chapter describes the results of the data analysis.

CHAPTER IV

DATA ANALYSIS

The research objectives of this study were to examine whether there are differences in persuasiveness of recommendations generated by different recommender systems, and what are the possible factors causing the differences. Persuasiveness was also compared for products of different complexity. As an important component of persuasion process in advertising, product involvement's influence on persuasiveness was examined to establish the relevance of the findings.

These research objectives were investigated in an experimental setting, where participants were exposed to all experimental conditions in the study. By separating the variance within subjects (differences between experimental conditions) from the variance between subjects (differences between participants), statistically significant differences between mean scores for the treatments could be obtained more accurately. This chapter presents the results of data analysis. Characteristics of the sample were described followed by a discussion of data analysis such as the manipulation checks, exploratory factor analysis, MANCOVA, and evaluation of the research hypotheses.

Sample Characteristics

Participants for the study were recruited from a Business Information Systems undergraduate class at Mississippi State University. The sample consisted of one hundred and fifty-seven undergraduate students and seven were excluded after the manipulation check. Boudreau et al. (2001) advocate the use of manipulation checks in experiments, to measure the extent to which treatments have been correctly perceived by the subjects. This allowed for exclusion of results from participants who had figured out the experiment condition and the purpose of the study. In this study, the manipulation checks were conducted at the end of data collection by asking students an open-ended question about the purpose of the study. Because of the repeated measures design of this study, the students had to answer the same set of questions for four different product searches. This may produce a learning effect and the answers to the early questions can influence their perception in the later searches so that the independence of the answers will be jeopardized. Seven students indicated that the study was to compare two different recommender systems, and were eliminated from data analysis. This reduced the sample size to one hundred and fifty.

The majority of the students were between eighteen and twenty-one (90.4%) years of age, with 91 males (58%) and 66 females (42%). Because the course is a lower level required course for business majors, most of the participants were non-senior students (freshman 29.3%, sophomore 43.3%, junior 24.8%). The dominant ethnicities of the students are white (81.5%) and African American (15.3%). Students were familiar with personal computers (mean of PC usage experience of 5-10 years) so the lack of experience with computer should not be considered as a problem. Although the students showed moderate familiarity with online shopping (mean of 4.01 on the 7 point Likert-scale), they were less experienced in using online recommender systems (mean=2.52 on the 7 point Likert-scale). These characteristics were compared with those before the manipulation check as summarized in Table 4.

Table 4. Sample Demographics

		N=150**	N=157**
Age	<18 18-21 >21	2 (1.3%) 137 (91.3%) 11 (7.4%)	2 (1.2%) 142 (90.4%) 13 (8.4%)
Gender	Male Female	88 (58.7%) 62 (41.3%)	91 (58%) 66 (42%)
Classification	Freshman Sophomore Junior Senior	46 (30.7%) 66 (44%) 35 (23.3%) 3 (2%)	46 (29.3%) 68 (43.3%) 39 (24.8%) 4 (2.5%)
Ethnicity	White African American Other	123 (82%) 22 (14.7%) 5 (3.3%)	128 (81.5%) 24 (15.3%) 5 (3.2%)
PC usage experience	X= 5-10 yrs, σ =1.8		X= 5-10 yrs, σ =1.8
Online shopping experience*	X= 4.05, σ =0.75		X= 4.01, σ =0.7
Recommender Systems experience*	X= 2.57, σ =1.74		X= 2.52, σ =1.64

* Online shopping experience and recommender systems experience were measured on a 7 point Likert-scale (1=not often, 7=very often).
** Sample size N was 157 before the manipulation check and 150 after the manipulation check.

Data Analysis

Scree Plot and Exploratory Factor Analysis

A pilot study of 30 students was conducted to test the measurement items used in the study. An exploratory factor analysis was used to assess the unidimensionality of the multi-item scales. The unidimensionality of a set of items used to measure a given construct is a necessary, but not sufficient, condition for construct validity. Construct validity was also assessed by examining the internal consistency, and convergent and discriminant validity of each construct. Factor analysis was used to assess unidimensionality and Cronbach's coefficient alpha was used to assess internal consistency.

A principle component factor analysis was performed using the thirty-two items to measure appropriateness, consistency, effectiveness, and product involvement. The criteria used to determine the number of factors to extract was an eigenvalue that was greater than or equal to one. The result indicated that five factors had eigenvalues exceeding 1.00. This was the number of factors used in this study.

Table 5. Exploratory Factor Analysis

Label	Consistency	Effectiveness	Appropriateness	Persuasiveness	Involvement
cnst1	0.843				
cnst2	0.770				
cnst3	0.740				
cnst4	0.735				
effec1		0.936			
effec2		0.971			
effec3			0.782		
effec4		0.731			
effec5		0.850			
effec6		0.939			
appr1			0.764		
appr2		0.775			
appr3		0.722			
appr4			0.895		
appr5			0.835		
persu1				0.969	
persu2				0.949	
persu3				0.943	
persu4				0.863	
persu5			0.587*	0.541*	
persu6				0.783	
persu7				0.731	
persu8				0.676	
persu9				0.818	
persu10				0.754	
persu11			0.756		
persu12				0.771	
invol1					0.883
invol2					0.837
invol3					0.776
invol4	0.862				

Note: * indicates items containing cross loadings.

Dimensionality of each of the factors was assessed by examining the factor loadings. Items with factor loadings greater than .50 on the factor with which they are supposed to load were considered adequate indicators of that factor (Hair, Anderson, Tatham, and Black, 1995).

The evaluation of dimensionality of items yielded both expected and unexpected results (Table 5). The items measuring consistency loaded only on one factor and all loadings exceeded .70. Five out of the six items measuring effectiveness loaded on one factor while the other loaded on appropriateness at .782, indicating it does not represent a single factor. Therefore, it was eliminated from the scale. The items that were supposed to measure appropriateness loaded on two factors instead of one. Two of the five items had significant loadings on effectiveness. The other three items loaded on one factor with loadings of .764, .895, and .835 respectively. The two items that loaded on effectiveness were eliminated from the scale.

Among the twelve items measuring persuasiveness, item five cross loaded on persuasiveness and appropriateness and item eleven loaded significantly on effectiveness. All other items loaded on one factor with significant loadings. Items five and eleven were eliminated from the scale. Three of the four items for product involvement loaded on one factor while item four loaded significantly on consistency. Item four was eliminated from the scale. A second factor analysis was performed with the remaining 27 items, as a result, item 3 in effectiveness (effect 3), items two and three in appropriateness (appr 2, appr3), item five in persuasiveness (persu5), and item four in product involvement (invol4) were eliminated. A review of factor loadings from the second analysis is presented in Table 6.

Table 6. Factor Analysis After Items Elimination

Item	Consistency	Effectiveness	Appropriateness	Persuasiveness	Involvement
cnst1	0.856				
cnst2	0.750				
cnst3	0.766				
cnst4	0.747				
effec1		0.928			
effec2		0.961			
effec4		0.729			
effec5		0.840			
effec6		0.929			
appr1			0.725		
appr4			0.883		
appr5			0.861		
persu1				0.953	
persu2				0.929	
persu3				0.931	
persu4				0.861	
persu6				0.803	
persu7				0.758	
persu8				0.718	
persu9				0.847	
persu10				0.779	
persu12				0.803	
invol1					0.920
invol2					0.908
invol3					0.854

Internal Consistency

Reliability had been defined as the “degree to which measures are free from error and therefore yield consistent results” (Peter, 1979). One aspect of reliability is internal consistency, which is an indicator of the level of homogeneity of a measuring scale (Cronbach, 1951). One criterion that has been widely used to assess the reliability of a multi-item measurement scale is Cronbach’s coefficient alpha. This statistical technique was used to assess the internal consistency of the model constructs. All five constructs (consistency, appropriateness, effectiveness, persuasiveness, and product involvement) had coefficient alpha values exceeding .7 (see Table 7). Nunnally suggested that a set of items with a coefficient alpha greater than .7 is considered internally consistent.

Table 7. Cronbach's Coefficient Alpha Values for Research Constructs

Constructs	Cronbach's Alpha
Consistency	0.910
Effectiveness	0.941
Appropriateness	0.907
Persuasiveness	0.947
Involvement	0.910

As discussed before, two other aspects of construct validity, convergent and discriminant validity were also assessed. The broader meaning of convergent validity has to do with the convergence of related scales and instruments. Convergent validity in this sense exists when the research proposed scale or measure of a given construct correlates with measures of the same construct using instruments proposed by other researchers. Convergent validity can also refer to the principle that the indicators of a given construct should be at least moderately correlated among themselves (Carmines, and Zeller, 1979). The result from the final factor analysis (see Table 6) indicated that all of the remaining factors had factor loadings greater than 0.5 on the factor they were supposed to load. These findings provided support for the convergent validity of the scales.

Discriminant validity refers to the principle that the indicators for different constructs should not be so highly correlated as to lead one to conclude that they measure the same thing (Campbell et al., 1959). An examination of cross-loading of items on multiple factors provided evidence about whether items discriminate between constructs. The results from the final factor analysis (see Table 6) showed that none of the remaining items had cross-loadings on more than one factor. Therefore, the constructs exhibited adequate discriminant validity.

MANCOVA

After elimination of cross-loading items and subjects that failed the manipulation check, the sum score for each experimental condition and participant was calculated. These results were analyzed with MANCOVA in a 2 x 2 factorial design with participants as block and product involvement as a covariate for persuasiveness. The results showed that the blocking for participants was effective ($p<0.001$). In other words, using the block design was effective in separating between-subject variance from within-subject variance. For persuasiveness, there was no interaction between recommender systems and product complexity ($p=0.22$), but significant difference between the two recommender systems ($p<0.001$). Product complexity had no statistically significant impact on recommendation persuasiveness ($p=0.58$). The effect of product involvement was also insignificant ($p=0.99$). The results of this analysis can be seen in Table 8. Similar results can be found for consistency, appropriateness, and effectiveness (see Table 8). Only participants and system made differences in consistency, effectiveness, and appropriateness. There was no interaction between system and product complexity for consistency, effectiveness, and appropriateness. Product involvement did not show a significant impact on consistency, effectiveness, and appropriateness.

Table 8. MANCOVA of Research Model

Source	Dependent Variable	Type III Sum of Square	df	Mean Square	F	Pr>F
Total (corr.)	appropriateness	8596.80	599			
	consistency	19819.20	599			
	effectiveness	25869.80	599			
	persuasiveness	80343.20	599			
Model	appropriateness	4014.58	153	26.24	2.55	<0.001*
	consistency	10623.44	153	69.43	3.37	<0.001*
	effectiveness	11225.82	153	73.37	2.23	<0.001*
	persuasiveness	56831.68	153	371.45	7.05	<0.001*
Participant	appropriateness	3569.05	149	23.95	2.33	<0.001*
	consistency	9965.9	149	66.86	3.24	<0.001*
	effectiveness	10200.05	149	68.46	2.08	<0.001*
	persuasiveness	54109.23	149	363.15	6.89	<0.001*
System	appropriateness	422.04	1	422.04	43.03	<0.001*
	consistency	651.04	1	651.04	31.85	<0.001*
	effectiveness	1011.40	1	1011.40	30.08	<0.001*
	persuasiveness	885.75	1	885.75	16.8	<0.001*
Complexity	appropriateness	0.38	1	0.38	0.04	0.85
	consistency	4.68	1	4.68	0.23	0.63
	effectiveness	13.20	1	13.20	0.40	0.53
	persuasiveness	16.45	1	16.45	0.31	0.58
System X Complexity**	appropriateness	0.38	1	0.38	0.04	0.85
	consistency	0.04	1	0.04	0.00	0.96
	effectiveness	0.20	1	0.20	0.01	0.94
	persuasiveness	81.4	1	81.4	1.54	0.22
Involvement	appropriateness	2.74	1	2.74	0.27	0.61
	consistency	1.73	1	1.73	0.08	0.77
	effectiveness	0.97	1	0.97	0.03	0.87
	persuasiveness	0.014	1	0.014	0.00	0.99
Error	appropriateness	4582.22	446	10.27		
	consistency	9195.76	446	20.63		
	effectiveness	14643.98	446	32.83		
	persuasiveness	23511.52	446	52.27		

Note: model with participants as block, product involvement as covariate, and system and complexity as main effects.
* significant ** interaction

When the model was evaluated again with only the recommender systems, and participants as blocks, both blocking and recommender systems retained their statistical significance, and product involvement remained insignificant (see Table 9). Both participants and system had p values less than 0.001 for persuasiveness, consistency, effectiveness, and appropriateness.

Table 9. MANCOVA of Research Model (without product complexity)

Source	Dependent Variable	Type III Sum of Square	df	Mean Square	F	Pr>F
Total (corr.)	appropriateness	8596.80	599			
	consistency	19819.20	599			
	effectiveness	25869.80	599			
	persuasiveness	80343.2	599			
Model	appropriateness	4014.21	151			
	consistency	10617.22	151	70.31	3.42	<0.001*
	effectiveness	11216.21	151	65.62	2.01	<0.001*
	persuasiveness	56733.90	151	375.72	7.13	<0.001*
Participant	appropriateness	3431.57	149	23.03	2.25	<0.001*
	consistency	9229.31	149	61.94	3.02	<0.001*
	effectiveness	9777.57	149	65.62	2.01	<0.001*
	persuasiveness	54274.14	149	364.26	6.91	<0.001*
System	appropriateness	442.20	1	442.20	43.23	<0.001*
	consistency	651.09	1	651.09	31.70	<0.001*
	effectiveness	1011.10	1	1011.10	30.91	<0.001*
	persuasiveness	885.94	1	885.94	16.81	<0.001*
Involvement	appropriateness	3.12	1	3.12	0.31	0.58
	consistency	0.23	1	0.23	0.01	0.92
	effectiveness	4.76	1	4.76	0.15	0.70
	persuasiveness	271	1	2.71	0.05	0.82
Error	appropriateness	4582.59	448	10.23		
	consistency	9201.97	448	20.54		
	effectiveness	14653.59	448	32.71		
	persuasiveness	23609.30	448	52.70		

Note: model with participants as block, product involvement as covariate, and system and complexity as main effects.
* significant

As shown in Table 10, subsequent comparison of means using the Least Significant Difference (LSD) demonstrated that the content-based recommender system showed statistically significant better appropriateness, consistency, effectiveness and persuasiveness than the collaborative filtering recommender system.

Table 10. Comparison of Means for Recommender Systems

	t-Grouping	Mean*	N**	System
Consistency	A	25.61	300	Content-based
	B	23.53	300	Collaborative
Effectiveness	A	24.45	300	Content-based
	B	21.85	300	Collaborative
Appropriateness	A	15.96	300	Content-based
	B	14.24	300	Collaborative
Persuasiveness	A	38.78	300	Content-based
	B	36.35	300	Collaborative
* denotes mean for groups with different letter are significantly different. ** N is number of subjects in each group.				

As product complexity did not show a significant impact on recommendation persuasiveness and there was no significant interaction between system and product complexity, the comparison of the means for combination of recommender system and product complexity was similar to those for comparison of groups using different systems. The result can be seen in Table 11. There were no differences between the means of persuasiveness, consistency, appropriateness, and effectiveness for combination groups using the same recommender systems although the products were of different complexity.

Table 11. Comparsion of Means for Recommender System & Product Complexity

	t-Grouping	Mean*	System
Consistency	A	23.60	Collaborative & DVD
		23.44	Collaborative & Notebook
	B	25.95	Content-based & DVD
		25.66	Content-based & Notebook
Effectiveness	A	26.60	Collaborative & DVD
		26.37	Collaborative & Notebook
	B	30.14	Content-based & DVD
		29.73	Content-based & Notebook
Appropriateness	A	24.21	Collaborative & DVD
		24.17	Collaborative & Notebook
	B	27.07	Content-based & DVD
		27.31	Content-based & Notebook
Persuasiveness	A	42.79	Collaborative & DVD
		44.23	Collaborative & Notebook
	B	47.05	Content-based & DVD
		46.49	Content-based & Notebook
* denotes mean for groups with different letters are significantly different.			

As stated in the previous chapter, the possibility of anchoring is a concern in a study with repeated measures design. Kahneman and Tversky (1974) compared mean responses after the anchor. In this study, two different recommender systems were alternated as the first one to be used for product searching. The anchoring was tested by comparing the means of persuasiveness for the content-based recommender system and collaborative filtering recommender system in the first and second position for each. In the case of the content-based recommender system, the means for persuasiveness in the first and in the second place did not differ significantly with a p-value of 0.925, but for the collaborative recommender system, the p-value was 0.0005, which showed a significant difference. These values were calculated with the paired t-test because of the close to normal distribution for the groups as evidenced by the histograms.

Finally, the relationships between persuasiveness and consistency, effectiveness, and appropriateness were evaluated. All factors (subject, effectiveness, and appropriateness) except consistency contribute significantly to the variance in persuasiveness with a R-square of 0.86. The results are summarized in Table 12.

Table 12. ANCOVA of Persuasiveness

Source	df	Sum of Square	Mean Square	F value	Pr>F
Total (corr)	599	80343.198			
Model	153	68895.13	450.30	17.54	<0.0001*
Consistency	1	2.76	2.76	0.11	0.743
Effectiveness	1	1134.15	1134.15	44.18	<0.0001*
Appropriateness	1	1389.97	139.97	54.15	<0.0001*
Involvement	1	1.52	1.52	0.06	0.81
Subject	149	34874.74	234.06	9.12	<0.0001*
Error	446	11448.06	25.67		
Note: model with participants as block and product involvement as covariate. * significant					

Although product involvement has been suggested as an important factor influencing response to online advertising, none of the tests in this study showed any significant impact. This may be caused by the control of the subject factor in the repeated measures design because Koufaris (2001-2002) indicated that product involvement is associated with the consumer. Therefore, the data did not provide an adequate foundation to assess the impact of product involvement on recommender system persuasiveness.

Evaluation of the Research Hypotheses

It is clear from the description of the data analysis that some but not all research hypotheses were supported. Results of the MANCOVA indicated that the different recommender systems led to different persuasiveness, but the persuasiveness was not influenced by product complexity. Furthermore, the impact of product involvement was not significant because of the extent of subject control in the repeated measures design. The first hypothesis tested whether types of recommender systems would influence recommendation persuasiveness. Analysis of the results showed that the persuasiveness of recommendation from different recommender systems differs significantly. Therefore, hypothesis H_1 is supported.

Research hypotheses H_{1a}, H_{1b}, and H_{1c} concerned the influence of types of recommender systems on appropriateness, consistency, and effectiveness. Content-based filtering recommender systems were hypothesized to have a higher degree of appropriateness and effectiveness, and collaborative filtering recommender systems were hypothesized to have a higher degree of consistency. As shown in the tables below, content-based filtering recommender systems have higher mean scores for appropriateness, effectiveness, and consistency. Therefore, H_{1a} and H_{1c} were supported and H_{1b} was not supported. It was clear that the scores for the three dependent variables for the two different recommender systems belong in different groups (see Tables 13-15).

Table 13. Comparison of Mean for H_{1a}

	t Grouping	Mean*	N	System
Appropriateness	A	15.96	300	Content-based
	B	14.24	300	Collaborative
* denotes mean for groups with different letters are significantly different. N=observations in group				

Table 14. Comparison of Mean for H_{1b}

	t Grouping	Mean*	N	System
Consistency	A	25.61	300	Content-based
	B	23.53	300	Collaborative
* denotes mean for groups with different letters are significantly different. N=observation in group				

Table 15. Comparison of Mean for H_{1c}

	t Grouping	Mean*	N	System
Effectiveness	A	24.45	300	Content-based
	B	21.85	300	Collaborative
* denotes mean for groups with different letters are significantly different. N=observation in group				

Hypothesis H_2 is related to the influence of product complexity on persuasiveness, effectiveness, consistency, and appropriateness. It was hypothesized that different levels of product complexity will lead to differences in the four dependent variables. The results showed no impact of product complexity on them (see Tables 16-19). Therefore, H_2, H_{2a}, H_{2b}, and H_{2c} were not supported. Part of the reason may lie in the relatively small differences in complexity between Notebook computer and DVD players.

Table 16. Comparison of Means for H_2

	t Grouping	Mean*	N	System
Persuasiveness	A	37.75	300	Notebook
	A	37.39	300	DVD player
* denotes mean for groups with same letters are not significantly different. N=observation in group				

Table 17. Comparison of Means for H_{2a}

	t Grouping	Mean*	N	System
Appropriateness	A	15.13	300	Notebook
	A	15.08	300	DVD player
* denotes mean for groups with same letters are not significantly different. N=observation in group				

Table 18. Comparison of Means for H_{2b}

	t Grouping	Mean*	N	System
Consistency	A	24.66	300	Notebook
	A	24.48	300	DVD player
* denotes mean for groups with same letters are not significantly different. N=observation in group				

Table 19. Comparison of Means for H_{2c}

	t Grouping	Mean*	N	System
Effectiveness	A	23.30	300	Notebook
	A	23.00	300	DVD player
* denotes mean for groups with same letters are not significantly different. N=observation in group				

Hypothesis H3 is to test the interaction between recommender systems and product complexity to affect persuasiveness, appropriateness, consistency and effectiveness. As there is no interaction witnessed in the MANCOVA test (see Tables 8), H3, H3a, H3b, and H3c were not supported.

The next research hypotheses concerned the persuasion theory, whether higher appropriateness, consistency and effectiveness of the recommendation lead to better persuasiveness. ANCOVA showed that consistency, effectiveness, and appropriateness together explained most of the variances in persuasiveness (85.75% with product involvement and 85.23% without product involvement). While effectiveness and appropriateness were significant factors in determining recommendation persuasiveness (both $p<0.0001$), consistency did not show statistical significance ($p=0.74$ with involvement and $p=0.98$ without involvement). Subject was a significant factor for recommendation persuasiveness. This proved the appropriateness of using subject controls in the study.

There are several significant findings in the study. First, system recommendations for non-experience product types are more persuasive than for collaborative filtering recommender systems. This includes higher scores for appropriateness, consistency, and effectiveness. Although the collaborative filtering system considers consumer purchasing history, it did not show better consistency in its recommendation as claimed. Product complexity was a non-significant factor in determining persuasiveness. Product involvement, which has been suggested as a possible influence factor, cannot be proved to have a significant impact on persuasiveness in this study.

In summary, the study was successful in confirming some, but not all, research hypotheses. The results of the evaluation of all hypotheses were summarized in Table 20. H_1, H_{1a}, H_{1c}, H_4, and H_5 are supported while the rest of the hypotheses are not supported by the data collected in the study.

Table 20. Summary of Hypothesis Testing

Hypothesis	Result
H1: Types of recommender systems influence recommendation persuasiveness.	Supported
H1a: Content-based filtering recommender systems will be perceived to have a higher degree of appropriateness than the collaborative filtering recommender systems.	Supported
H1b: Collaborative filtering recommender systems will be perceived to have a higher degree of consistency than content-based filtering recommender systems.	Not supported
H1c: Content-based filtering recommender systems will be perceived to have a higher degree of effectiveness than the collaborative filtering recommender systems.	Supported
H2: Product complexity influence recommendation persuasiveness.	Not supported
H2a: Product complexity influence recommendation appropriateness.	Not supported
H2b: Product complexity influence recommendation consistency.	Not supported
H2c: Product complexity influence recommendation effectiveness.	Not supported
H3: Product complexity interacts with types of recommender systems in affecting recommendation persuasiveness.	Not supported
H3a: Product complexity interacts with types of recommender systems in affecting recommendation appropriateness.	Not supported
H3b: Product complexity interacts with types of recommender systems in affecting recommendation consistency.	Not supported
H3c: Product complexity interacts with types of recommender systems in affecting recommendation effectiveness.	Not supported
H4: Recommendation appropriateness will be positively associated with the recommender system's persuasiveness.	Supported
H5: Recommendation consistency will be positively associated with the recommender system's persuasiveness.	Not supported
H6: Recommendation effectiveness will be positively associated with the recommender system's persuasiveness.	Supported

CHAPTER V

CONCLUSION AND IMPLICATIONS

Research on online recommender systems has focused on the statistical accuracy of the algorithms driving the system, with little emphasis on interface issues and the user perspective. Some recent studies have explored the impact of transparency (Herlocker et al., 2000), explanation (Wang et al., 2004; Ye et al., 1995), trust (Wang, and Benbasat, 2005) on acceptance of recommendations given by recommender systems but none of them has compared those influences in different systems. In this study, a new concept, the persuasiveness of recommendations given by two types of recommender systems, was compared. Based on Reardon's persuasion theory, the underlying reasons for the differences were investigated.

The two types of recommender systems, the content-based and the collaborative filtering recommender systems did show significant differences in persuasiveness. The recommendation given by the content-based recommender systems are more believable, credible and trustworthy to the consumers searching for products. The better recommendation from the content-based recommender systems was also more appealing to the consumers because they provided affective and stimulating information matching the consumer needs. The content-based recommender system showed higher scores for all three dimensions of persuasiveness introduced by Reardon. By asking customer input of product features and customer preferences, the content-based recommender system clarified the customer needs and requirements. By arranging the best-match recommendation next to the preferred specifications, the system made the reasoning process and logic transparent to the customers so that they can tell whether their requirements have been met. Therefore, they can determine whether the recommendation was appropriate and effective compared with their explicit needs. The content-based recommender system was better in revealing the ties between customer needs and product recommendation. This made the recommendations more persuasive to the customer.

Although the collaborative filtering recommender system provided a way to help product search when customers were not sure or cannot clearly express their requirements or preferences, the system scored lower on consistency than did the content-based systems. The way the system soliciting customer preference did not present the criteria or rules the system used to search for what the like-minded people want. Therefore, the customer cannot determine whether the recommended products were consistent to their taste/preference or existing knowledge. This is different from H1b. Although a content-based recommender system did not consider information of like-minded people, it still showed better consistency in matching recommendations with customer guidance. Instead of getting their existing knowledge and taste from the products rating, the product features were considered to be a good representation of consumer preferences, which is more explicit and accurate for the kind of product selected for the current study.

Although studies (Charlet, 1998a) have suggested that the collaborative filtering recommender systems are more appropriate for searching experience goods like books, CDs, and movies, amazon.com has claimed its recommender system capability in search of most products. The results from this study showed that for non-experience products, the content-based recommender systems were perceived to be more persuasive by providing more appropriate, more effective, and more consistent recommendations.

When using recommender systems to give personalized product recommendations for consumers, online retailers should make sure that the types of systems are appropriate for the product types. For non-experience products for which the product attributes can be explicitly expressed, content-based recommender systems can provide more persuasive recommendations. While the use of collaborative filtering recommender systems for non-experience products leads to less persuasive recommendations, its repeated occurrence can have a negative impact on consumer perception of an online retailer and an online store. Consumers will look for other online stores that can provide more persuasive recommendations. Therefore, to fully realize the intended purpose of their recommender systems, online retailers should tailor the recommender systems used for different product categories so that persuasive recommendations could be obtained by consumers visiting their online store.

Product complexity did not show significant impact on recommendation persuasiveness even though it has been suggested as a factor reducing the effectiveness and accuracy of complex consumer decision-making (Keller et al., 1987). There are two explanations for this outcome. First, the recommender systems have effectively reduced the complexity of the decision making for consumer product search by information filtering and priority management. The amount of alternatives and attributes associated with a product is no longer a burden to the consumer. The second reason could be the small differences of product complexity between products used in the study. Therefore, there is a wide range of products with different complexity that online retailers can use for their recommender systems. The recommender system can be a good tool to alleviate the barriers in selling complex product online.

According to Reardon's (1981) persuasion theory, appropriateness, consistency, and effectiveness of a persuasion message can determine the persuasiveness of the message when people are motivated to reason and are capable of reasoning about the alternatives presented. The result of the study showed a significant difference between the consistency of the recommendation given by the two recommender systems, and yet it was not a significant factor in determining message persuasiveness. Appropriateness and effectiveness of the persuasion message can be easily communicated to the consumer by detailed explanation mechanism and comparison between the consumer input and recommendation output.

Compared to appropriateness and effectiveness, consistency is a factor that is more difficult for consumers to evaluate. It is hard to explain explicitly and can involve different criteria. Although the collaborative filtering recommender systems are designed to connect consumer past purchasing history or preference of like-minded people with the recommended product, most of them were not able to demonstrate a logic link between the consumer input and system recommendation. Consistency can be an insignificant determinant of persuasiveness when the search product is non-experience goods and the consumer needs can be materialized into specific attributes. Online retailers should try to avoid using collaborative filtering recommender systems for personalized product recommendation for non-experience goods. When using collaborative filtering recommender systems for experience goods, a good presentation of the reasoning logic should be helpful for consumers to accept the system recommendation. The usefulness of consistency for persuasion message needs to be determined by further study.

Appropriateness and effectiveness are two criteria that can be used by online retailers to assess their online recommender systems persuasiveness. These differ from usefulness and ease of use when evaluating online recommender systems acceptance. They provide a complementary set of measurements that can help online retailers improve the effectiveness and efficiency of their online recommender systems. Therefore, appropriate recommender systems could be implemented for the suitable products categories to achiever better product targeting. For example, when a consumer asks the recommender system to search for a non-experience product, a content-based recommender system will be started asking for product attributes and specifications. If an experience product was input for searching, a collaborative filtering recommender system will be engaged for preference searching either by giving a list of products for rating or by considering the consumer's past history for clues to potential choices. Providing collaborative filtering recommender systems for recommendation of all product categories can lead to unsatisfied customers. The negative impression of an unpersuasive recommendation could affect the future utilization of the recommender system. This can lead to underutilization of the recommender systems invested by the online retailers and drive the potential customers to competitor sites.

When searching for products of different complexity, the two recommender systems did not show significant difference in persuasiveness. The use of recommender systems by online retailers can help consumers dealing with complex information. The recommender systems help the consumers overcome the difficulties in processing information associated with products of high complexity. By filtering and prioritizing product information of customer preference, the consumers were able to reach quick decisions with adequate accuracy. If the recommender systems were well-matched with the appropriate product categories, retailers can effectively increase the kinds of product that could be marketed online.

In addition to the practical implications, this study contributes to knowledge about persuasiveness in the IS community. Although persuasiveness has been a well-researched subject in communication (Block, and Keller, 1997; Pornpitakpan, 2004; Strahan, Spencer, and Zanna, 2002), psychology , and advertising in marketing (Anand, and Sternthal, 1992; Komiak et al., 2004; Lowrey, 1998), it is new in IS research. Persuasiveness provides another perspective for IS research that extends this concept from interpersonal interaction to human-computer interaction. This enriches the widely used technology acceptance models. The last decade has seen phenomenal growth and improvement in the capabilities of computer-based information systems, especially the internet based applications, yet the full utilization of the technology capabilities are limited by the human component in the chain. Therefore, it is important to introduce new concepts in understanding the human behavior so that the weakest link can be strengthened for better technology adoption and utilization.

The use of repeated measures design is another contribution of the research. With this design, the subject factor in the persuasive communication can be controlled so as to isolate the persuasion message. This is not feasible with other studies before. The successful control of the subject factor can be proved by the result about the covariate used.

Product involvement has been suggested as an influencing factor for cognitive and behavioral response to online advertising in marketing research. It can affect consumer information search style, process motivation, and understanding of the message (Ahn et al., 2002; Cho et al., 1999; Karson et al., 2001; Laczniak et al., 1999; Yoo et al., 2001). Product involvement varies for each customer (Koufaris et al., 2001-2002). The current study showed that persuasiveness as well as its three inducements (appropriateness, consistency, and effectiveness) differs significantly between subjects but product involvement did not show significant impact on them. Because of the repeated measures design, the variance caused by the difference in product involvement has been expressed in the subject factor and there is no single factor effect shown for product involvement. Therefore, this design alleviated the difficulties in isolating the multiple factors in the persuasion process and concentrated on the study of persuasion message development and presentation by different recommender systems.

Limitations and Future Research

Every study has its strengths and weaknesses, and this study is no exception. One of the weaknesses in experimental designs is limited realism to the participants. Even though students are the largest population group for online shopping, they cannot completely surrogate the actual online customer population. Participants in the main sample were primarily undergraduate students under the age of 21. Though the products used in the experiment were picked from the focus group as the most likely online purchase items for college students, there is no limit set for the prices and affordability for the two products. It can reasonably be expected that only a few had real need for the product searched which might affect their information search behavior and perception of the recommendation persuasiveness. The levels of complexity of the two products chosen are comparatively close which may contribute to the insignificant impact of product complexity on persuasiveness. In future studies, different population samples and different products can be used.

The sample was also very homogenous with respect to age and level of education, and the same study with participants significantly different in age or education could have produced different results. The students' average experience with online recommender systems is at the lower end but there are several participants who have used the recommender system very often. Since experience with recommender systems is not a factor considered in this study, their answers can skew the overall response to the survey questions. Until the study has been repeated with a significantly different sample, the generalization will remain low.

A further limitation of this study is the carryover effect. The carryover effect is an inherent problem with repeated measures design. The results of the study showed that for the collaborative filtering recommender system, the participants showed a significant difference toward recommendation persuasiveness when the system was used first and second for product search. This brought possible bias to the results due to the learning participants gained in using the systems repeatedly. Future studies could use the randomized design with identical subject groups so that different experiment treatments could be given to each subject only once to eliminate the carryover effect. In this new design, product involvement can be added as a third treatment which is not feasible in a repeated measures design.

The use of existing websites with different recommender systems also introduced limitations to the study. While the use of existing sites added more realism to the study, many non-recommender system factors can be introduced. Although the cookies were disabled and participants were asked to register as new users every time starting a new search, there were obvious differences in familiarity with the websites used according to the time students spent on the experiment tasks. Even though very few students said they have used the recommender systems, their previous experience with other functions at the websites can affect their response to the questionnaires in the current study. Future studies could try building new recommender systems with different algorithms and technologies rather than using ones that are currently available from commercial websites. This ensures that the agent would be new to all participants and the study would remain focused on the initial differences in the system.

Due to the advances in web-based technologies and the explosive amount of information available to consumers, more companies are using online recommender systems to provide personalized product information to their customers. However, because of the high risk and uncertainties associated with online environment, consumers must be convinced when doing product search or actual purchase online. According to Wang and Benbasat (2005), recommender systems are treated as "social actors" with human characteristics. Therefore, the persuasion theories in the interpersonal domain may generally apply to persuasiveness in technological artifacts. More research is needed to examine other factors in the persuasion process such as trust, source credibility, consumer self-confidence. For example, Wang and Benbasat (2003) have explored that consumer trust in the recommender system as "virtual assistants" are important in consumers' intentions to adopt online recommenders systems.

Studies suggested that consumers' social relationship with online stores could be strengthened by further interactions. Additional interaction with the online store may reduce consumers' perception of uncertainty and risk in using them (Gefen et al., 2003). This may apply to persuasiveness of recommender systems. The insignificance of consistency for persuasiveness in the current study may be caused by the omission of time factor. Additional research is needed to investigate the importance of consistency and change of persuasiveness over time.

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APPENDIX

A. RECOMMENDER SYSTEM EXPERIMENT SURVEY

INSTRUCTIONS

Thank you for participating in this experiment. Your answers are important for the study. Please be candid and cooperative in the experiment and return the completed survey when you leave the classroom. Don't discuss about the experiment during or after the session. Sign on both page of the Informed Consent form and keep one copy for your own reference.

In the entire computer experiment, you are expected to perform as quickly and as accurately as possible. A 5 minute training session will be conducted before the computer experiment. Definitions frequently used in the questionnaire are provided on the next page.

The experiment consists of four different tasks, and instructions for each task are presented before the start of each task. You should follow the instructions for each task. Please do not open or close any windows for purposes not related to the experiment.

In all of the surveys you are to complete today, we ask questions that make use of rating scales with 7 places. Please **circle a number** which represents your perception of the recommender system you just used. For example, if you believe that WebCT is a good learning tool and would like to take another course using WebCT in the future, you might respond to the statement below by circling the corresponding number.

	Strongly Disagree						Strongly Agree
1. I would like to enroll in a course using WebCT next semester.	1	2	3	4	5	6	7

You can now start the experiment.

DEFINITIONS

1) **Recommender systems** are the interactive decision support systems that assist you in the initial screening of alternatives available in online stores and provide recommendations for product search and selection.

2) **Appropriateness** refers to your perception of the fitness and desirability of recommendations given by the recommender system.

3) **Consistency** refers to whether the recommendations from a recommendation system are consistent with your existing knowledge.

4) **Effectiveness** refers to the perceived degree of the recommender system's ability to clearly understand and address your need and concerns.

5) **Persuasiveness** refers to the extent to which you are moved or influenced by the recommender system's reasoning to a belief that the recommended products best fit your personal needs.

TASK 1

1. Open the browser Internet Explorer;

2. Visit **http://www.activebuyersguide.com** by typing in the website address;

3. Search for **a Notebook computer** you plan on purchasing soon by going to the **Notebook computer category**;

4. Choose the product attributes you think is the most important to you from the product attributes given;

5. Click **recommend**;

6. Viewing the recommended product which is marked as "**best match**";

7. If the system cannot find a product for your preference, adjust the preference criteria and search again;

8. Complete the questions on the next pages.

Consistency

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
1. The product recommendation is consistent with your guidance.	1	2	3	4	5	6	7
2. The recommendation output is consistent with entry requirement.	1	2	3	4	5	6	7
3. The information in the recommend-ation appears to be consistent with human stereotypes.	1	2	3	4	5	6	7
4. Where rating, symbols, product categories etc. are used, they are consistent with your ability to understand.	1	2	3	4	5	6	7
5. The wording of the recommend-ation is familiar to you.	1	2	3	4	5	6	7

Effectiveness

1. The recommender system was able to convince me that it understands my unique need and concerns.	1	2	3	4	5	6	7
2. The recommender system was able to work out recommendations to my questions or objections.	1	2	3	4	5	6	7
3. The recommender system communicates the product recommendations clearly and concisely.	1	2	3	4	5	6	7
4. The recommender system makes effective use of aids (charts, pictures, audio-visuals) to improve the recommendation.	1	2	3	4	5	6	7

5. The recommendation makes me want to buy things from this site again.	1	2	3	4	5	6	7
	Strongly Disagree						Strongly Agree
6. The recommender system demonstrates identification and understanding of my real need and concerns.	1	2	3	4	5	6	7

Appropriateness

Over all the recommendations given by the recommender systems are:

1. rational	1	2	3	4	5	6	7
2. informative	1	2	3	4	5	6	7
3. deal with facts	1	2	3	4	5	6	7
4. knowledgeable	1	2	3	4	5	6	7
5. logical	1	2	3	4	5	6	7

Persuasiveness

Over all the recommendation given by the recommender systems are:

1. believable	1	2	3	4	5	6	7
2. credible	1	2	3	4	5	6	7
3. trustworthy	1	2	3	4	5	6	7
4. reliable	1	2	3	4	5	6	7

5.	dependable	1	2	3	4	5	6	7
6.	affects my feelings	1	2	3	4	5	6	7
7.	touch me emotionally	1	2	3	4	5	6	7
8.	stimulating	1	2	3	4	5	6	7
9.	reach out to me	1	2	3	4	5	6	7
10.	stirring	1	2	3	4	5	6	7
11.	moving	1	2	3	4	5	6	7
12.	exciting	1	2	3	4	5	6	7

Task 2

1. Open the browser Internet Explorer;

2. Visit **http://www.amazon.com** by typing the website address given;

3. Go to "**personalized recommendation**" and register **as a new user** by entering your email address. Use a different email address if you have registered at amazon.com before;

4. Enter you name and password;

5. Click on "**start recommendation wizard**";

6. Check the store category "Computers" and continue;

7. Type in a computer type **OR** a trusted brand you plan on purchasing soon, and continue;

8. Go through **all relevant items** provided and check detail specifications and explanations if needed. Don't rate any item before checking the details because the saved rating will disappear!

9. Rate **relevant items** given by clicking on the star-scale for each item. Click on " **rate more items**" if you think it is necessary;

10. Click **finish** to see your recommendations;

11. View the product that matches your choice by checking the product specification from the recommendation list;

12. Complete the questions on the next pages.

Consistency

	Strongly Disagree						Strongly Agree
1. The product recommendation is consistent with your guidance.	1	2	3	4	5	6	7
2. The recommendation output is consistent with entry requirement.	1	2	3	4	5	6	7
3. The information in the recommendation appears to be consistent with human stereotypes.	1	2	3	4	5	6	7
4. Where rating, symbols, product categories etc. are used, they are consistent with your ability to understand.	1	2	3	4	5	6	7
5. The wording of the recommend-ation is familiar to you.	1	2	3	4	5	6	7

Effectiveness

1. The recommender system was able to convince me that it understands my unique need and concerns.	1	2	3	4	5	6	7
2. The recommender system was able to work out recommendations to my questions or objections.	1	2	3	4	5	6	7
3. The recommender system communicates the product recommendations clearly and concisely.	1	2	3	4	5	6	7

4. The recommender system makes effective use of aids (charts, pictures, audio-visuals) to improve the recommendation.	1	2	3	4	5	6	7
5. The recommendation makes me want to buy things from this site again.	1	2	3	4	5	6	7

	Strongly Disagree						Strongly Agree
6. The recommender system demonstrates identification and understanding of my real need and concerns.	1	2	3	4	5	6	7

Appropriateness

Over all the recommendations given by the recommender systems are:

1. rational	1	2	3	4	5	6	7
2. informative	1	2	3	4	5	6	7
3. deal with facts	1	2	3	4	5	6	7
4. knowledgeable	1	2	3	4	5	6	7
5. logical	1	2	3	4	5	6	7

Persuasiveness

Over all the recommendation given by the recommender systems are:

1. believable	1	2	3	4	5	6	7
2. credible	1	2	3	4	5	6	7
3. trustworthy	1	2	3	4	5	6	7
4. reliable	1	2	3	4	5	6	7

5. dependable	1	2	3	4	5	6	7
6. affects my feelings	1	2	3	4	5	6	7
7. touch me emotionally	1	2	3	4	5	6	7
8. stimulating	1	2	3	4	5	6	7
9. reach out to me	1	2	3	4	5	6	7
10. stirring	1	2	3	4	5	6	7
11. moving	1	2	3	4	5	6	7
12. exciting	1	2	3	4	5	6	7

Task 3

1. Open the browser Internet Explorer;

2. Visit **<u>http://www.amazon.com</u>** by typing the website address given;

3. Go to "**personalized recommendation**" and register **as a new user** by entering your email address. Use a different email address if you have registered at amazon.com before;

4. Enter you name and password;

5. Click on "**start recommendation wizard**";

6. Check the store category "Electronics" and continue;

7. Type in DVD player **<u>OR</u>** a trusted brand of electronics you plan on purchasing soon, and continue;

8. Go through **all** items provided and check detail specifications and explanations if needed. Don't rate any item before checking the details because the saved rating will disappear!

9. Rate all items given by clicking on the star-scale for each item. Click on "rate more items" if you like;

10. Click **finish** to see your recommendations;

11. View the product that matches your choice by checking the product specification from the recommendation list;

12. Complete the questions on the next pages.

Consistency

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
1. The product recommendation is consistent with your guidance.	1	2	3	4	5	6	7
2. The recommendation output is consistent with entry requirement.	1	2	3	4	5	6	7
3. The information in the recommendation appears to be consistent with human stereotypes.	1	2	3	4	5	6	7
4. Where rating, symbols, product categories etc. are used, they are consistent with your ability to understand.	1	2	3	4	5	6	7
5. The wording of the recommend-ation is familiar to you.	1	2	3	4	5	6	7

Effectiveness

1. The recommender system was able to convince me that it understands my unique need and concerns.	1	2	3	4	5	6	7
2. The recommender system was able to work out recommendations to my questions or objections.	1	2	3	4	5	6	7
3. The recommender system communicates the product recommendations clearly and concisely.	1	2	3	4	5	6	7

4. The recommender system makes effective use of aids (charts, pictures, audio-visuals) to improve the recommendation.	1	2	3	4	5	6	7
	Strongly Disagree						Strongly Agree
5. The recommendation makes me want to buy things from this site again.	1	2	3	4	5	6	7
6. The recommender system demonstrates identification and understanding of my real need and concerns.	1	2	3	4	5	6	7

Appropriateness

Over all the recommendations given by the recommender systems are:

1. rational	1	2	3	4	5	6	7
2. informative	1	2	3	4	5	6	7
3. deal with facts	1	2	3	4	5	6	7
4. knowledgeable	1	2	3	4	5	6	7
5. logical	1	2	3	4	5	6	7

Persuasiveness

Over all the recommendation given by the recommender systems are:

1. believable	1	2	3	4	5	6	7
2. credible	1	2	3	4	5	6	7
3. trustworthy	1	2	3	4	5	6	7
4. reliable	1	2	3	4	5	6	7

5. dependable	1	2	3	4	5	6	7
6. affects my feelings	1	2	3	4	5	6	7
7. touch me emotionally	1	2	3	4	5	6	7
8. stimulating	1	2	3	4	5	6	7
9. reach out to me	1	2	3	4	5	6	7
10. stirring	1	2	3	4	5	6	7
11. moving	1	2	3	4	5	6	7
12. exciting	1	2	3	4	5	6	7

Task 4

1. Open the browser Internet Explorer;

2. Visit **http://www.activebuyersguide.com** by typing in the website address;

3. Search for a **DVD player** you plan on purchasing soon by going to the **DVD player category**;

4. Choose the product attributes you think is the most important to you for the product attributes given;

5. Click **recommend**;

6. Viewing the recommended product which is marked as "**best match**";

7. If the system cannot find a product for your preference, adjust the preference criteria and search again;

8. Complete the questions on the next pages.

Consistency

	Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
1. The product recommendation is consistent with your guidance.	1	2	3	4	5	6	7
2. The recommendation output is consistent with entry requirement.	1	2	3	4	5	6	7
3. The information in the recommendation appears to be consistent with human stereotypes.	1	2	3	4	5	6	7
4. Where rating, symbols, product categories etc. are used, they are consistent with your ability to understand.	1	2	3	4	5	6	7
5. The wording of the recommendation is familiar to you.	1	2	3	4	5	6	7

Effectiveness

1. The recommender system was able to convince me that it understands my unique need and concerns.	1	2	3	4	5	6	7
2. The recommender system was able to work out recommendations to my questions or objections.	1	2	3	4	5	6	7
3. The recommender system communicates the product recommendations clearly and concisely.	1	2	3	4	5	6	7

4. The recommender system makes effective use of aids (charts, pictures, audio-visuals) to improve the recommendation.	1	2	3	4	5	6	7
	Strongly Disagree						Strongly Agree
5. The recommendation makes me want to buy things from this site again.	1	2	3	4	5	6	7
6. The recommender system demonstrates identification and understanding of my real need and concerns.	1	2	3	4	5	6	7

Appropriateness

Over all the recommendations given by the recommender systems are:

1. rational	1	2	3	4	5	6	7
2. informative	1	2	3	4	5	6	7
3. deal with facts	1	2	3	4	5	6	7
4. knowledgeable	1	2	3	4	5	6	7
5. logical	1	2	3	4	5	6	7

Persuasiveness

Over all the recommendation given by the recommender systems are:

1. believable	1	2	3	4	5	6	7
2. credible	1	2	3	4	5	6	7
3. trustworthy	1	2	3	4	5	6	7
4. reliable	1	2	3	4	5	6	7

5. dependable	1	2	3	4	5	6	7
6. affects my feelings	1	2	3	4	5	6	7
7. touch me emotionally	1	2	3	4	5	6	7
8. stimulating	1	2	3	4	5	6	7
9. reach out to me	1	2	3	4	5	6	7
10. stirring	1	2	3	4	5	6	7
11. moving	1	2	3	4	5	6	7
12. exciting	1	2	3	4	5	6	7

Product Involvement

Using the following scale, please indicate how much you:

Notebook Computer	very little						very much
1. use Notebook computer	1	2	3	4	5	6	7
2. are involved with Notebook Computer	1	2	3	4	5	6	7
3. are a Notebook computer expert	1	2	3	4	5	6	7
4. are interested in Notebook computer, relative to other people	1	2	3	4	5	6	7

DVD Player

1. use DVD player	1	2	3	4	5	6	7
2. are involved with DVD player	1	2	3	4	5	6	7
3. are a DVD player expert	1	2	3	4	5	6	7
4. are interested in DVD player, relative to other people	1	2	3	4	5	6	7

Demographics

1. What is your age? _______________ years old.

2. What is your gender? (Please circle one)

   Male Female

3. What is your program? (Please circle one)

   Freshman Sophomore Junior Senior Graduate

4. What is your ethnicity? (Please circle one)

   White/Caucasian African American Asian/Asian Islander Other

5. Which one best describe your computer usage experience? (Please circle one)

   <1 year 1- <5 years 5-10 years >10 years

	Strongly Disagree						Strongly Agree
6. I have purchased products/services through the Internet very often.	1	2	3	4	5	6	7
7. I have used the recommender systems very often when buying things online.	1	2	3	4	5	6	7

8. What do you think the purpose of this experiment is?

Thank you for your participation!